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Research Article

Mapping The Intellectual Structure of AI in Tuberculosis Research: A Keyword Co-occurrence and Bibliometric Analysis

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ABSTRACT

Artificial intelligence (AI) has become increasingly essential in global tuberculosis (TB) control, offering advances in diagnostic accuracy, drug-resistance prediction, treatment monitoring, and public health decision-making. As research activity accelerates, a structured bibliometric assessment is necessary to map scientific progress and highlight emerging directions. This study conducted a bibliometric analysis using data retrieved from Scopus, from which 57 articles were included after rigorous cleaning and screening. Citation metrics were computed using Publish or Perish, while VOSviewer was employed to visualize keyword co-occurrence networks. Citation impact was evaluated using total local citation score (TLCS) and total global citation score (TGCS). Findings show that annual publication output remained low until 2023 but increased sharply from 2023 to 2025, reflecting rapid global expansion of AI-related TB research. The Indian Journal of Tuberculosis and the International Journal of Biomedical Imaging emerged as influential journals, with the latter demonstrating the highest TGCS, underscoring its broad international impact. Despite this global momentum, collaboration among authors remains limited, with several isolated research clusters rather than a unified network. Keyword analysis revealed major themes centered on AI-assisted TB prediction, AI for monitoring treatment responses and drug-resistant TB patterns, machine-learning models developed for TB screening, and digital platforms and remote health technologies into TB management and disease prevention. Overall, AI research in TB is expanding rapidly, driven by global recognition of AI as a critical instrument for accelerating detection, optimizing treatment strategies, and strengthening TB control efforts worldwide.

Keywords: *Artificial intelligence, tuberculosis management, bibliometric analysis, predictive machine learning*

INTRODUCTION

Tuberculosis (TB) remains one of the most persistent global health challenges, with progress plateauing in many high-burden regions due to delayed diagnosis, rising drug resistance, and inconsistent treatment adherence (Prasetyo et al., 2025b). Conventional TB control systems depend heavily on laboratory capacity, skilled personnel, and reliable follow-up—resources that are frequently limited in real-world settings (Prasetyo et al., 2025a). These operational gaps have pushed artificial intelligence (AI) into the conversation as a practical (Mariani et al., 2023), scalable tool capable of strengthening weak points across the TB care continuum.

Over the past decade, AI has moved from experimental curiosity to functional support technology (Damioli et al., 2025). Deep learning models now assist in automated chest X-ray interpretation for large-scale screening, especially where radiologists are scarce (Guo et al., 2024). Machine learning algorithms are being applied to genomic, radiological, and clinical data to detect drug resistance, stratify risk, and support clinical decisions. Predictive analytics are used to forecast transmission patterns and optimize resource allocation (Haga, 2024). AI-enabled digital adherence platforms can track dosing behavior and flag early non-adherence, offering monitoring capacity traditional systems simply cannot match (Babel et al., 2021) . These advances make it clear that AI is no longer confined to diagnostics—it is shaping surveillance, case management, and health-system planning.

The scientific output reflects this rapid expansion. Research now spans radiology, computational biology, epidemiology, digital health, implementation science, and public health (He et al., 2024). High-income countries dominate algorithm development, while high-burden regions contribute increasingly to applied and field-based studies (Yang et al., 2024). Despite this momentum, the literature remains scattered, methodologically diverse, and uneven in quality. Datasets vary widely, evaluation protocols are inconsistent, and many studies lack meaningful real-world validation (Goetz et al., 2024). Because of this fragmentation, it is difficult to determine where genuine progress is happening and where the field is simply accumulating publications without translational impact (IOANNIDIS, 2016).

In a landscape this broad and fast-moving, keywords become more than metadata—they are the clearest signal of how the scientific community conceptualizes the field. Keyword patterns capture the core ideas, methods, and priorities driving AI–TB research: deep learning, drug resistance prediction, chest X-ray screening, digital adherence, epidemiological modelling, and beyond. Analyzing keyword co-occurrence and its evolution over time exposes how research themes cluster, mature, or emerge(Narong & Hallinger, 2023). This thematic mapping is crucial for understanding intellectual structure, identifying neglected areas, and differentiating between truly growing research fronts and short-lived trends. In bibliometric studies, keyword analysis is one of the strongest tools for uncovering the conceptual backbone of a field (Kumar, 2025).

While the volume of AI related TB literature has greatly expanded in recent years, the current landscape remains highly fragmented across disparate disciplines, varying methodological quality, and inconsistent evaluation standards. Therefore, a keyword co-occurrence analysis is specifically needed to map the underlying intellectual structure, trace shifting research fronts, and expose conceptual blind spots—such as the operational disconnect between diagnostic algorithm development and real-world implementation (Kumar, 2025). Addressing this gap, the study offers novelty by utilizing VOSviewer to map multi-cluster keyword co-occurrences up to 2025. By synthesizing thematic clusters alongside global impact metrics, this study provides a structured framework that identifies neglected research priorities, clarifies cross-disciplinary trajectory, and guides the actionable integration of AI into global TB control systems.

MATERIAL AND METHODS

Relevant studies were retrieved from the Scopus database on August 28, 2025, selected for its comprehensive indexing of peer-reviewed biomedical and technological literature and consistent metadata structure (Schotten et al., 2017). The search covered all years from the database's inception to August 2025. The search strategy targeted publications on AI and TB using the following terms: *("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("tuberculosis" OR "TB" OR "Mycobacterium tuberculosis" OR "pulmonary tuberculosis" OR "TB diagnosis" OR "TB screening") AND ("health management"OR "health maintenance" OR "healthcare management" OR "disease management").*

Eligibility Criteria and Justification

To ensure data quality and methodological consistency, specific eligibility parameters were applied. Several inclusion criteria were involved:

1. Original research articles applying AI, machine learning, or digital intelligence tools to any aspect of TB detection, diagnosis, prediction, surveillance, or management.
2. When duplicate records appeared, the earliest and most complete version was retained.
3. Only English-language publications were included.

To optimize the related articles, some exclusion criteria were adapted:

1. Publication Types: News items, conference proceedings, editorials, reviews, book chapters, and case reports were excluded. Conference papers and preprints were omitted due to their variable peer-review rigor and potential metadata incompleteness in citation mapping.
2. Language Restrictions: Non-English publications were excluded to ensure accurate thematic parsing, standardized keyword translation, and consistent semantic interpretation during natural language processing and network mapping.
3. Accessibility: Articles lacking full-text availability or essential indexing metadata were removed.

Data Processing and Keyword Normalization

All retrieved records were exported in .CSV and .RIS formats. Data cleaning was conducted to standardize author names, institutional affiliations, and keyword variants. A unified thesaurus file was created to normalize synonymous keywords prior to network generation. Two researchers independently screened all titles and abstracts, followed by full-text evaluation. Inter-rater discrepancies were resolved through discussion until 100% consensus was reached.

Bibliometric Analysis and VOSviewer Settings

Descriptive citation metrics—including Total Local Citation Score (TLCS) and Total Global Citation Score (TGCS)—were calculated using Publish or Perish to evaluate publication volume and journal impact. First, Publish or Perish, a citation analysis tool that retrieves and processes academic data from multiple scholarly databases, was used to assess citation patterns, identify influential authors, journals, and articles, and quantify the historical development of research in AI-related TB studies (Harzing, 2025). Publish or Perish enabled the generation of structured citation metrics and comparative tables, providing a clear view of how scholarly influence has evolved across the field.

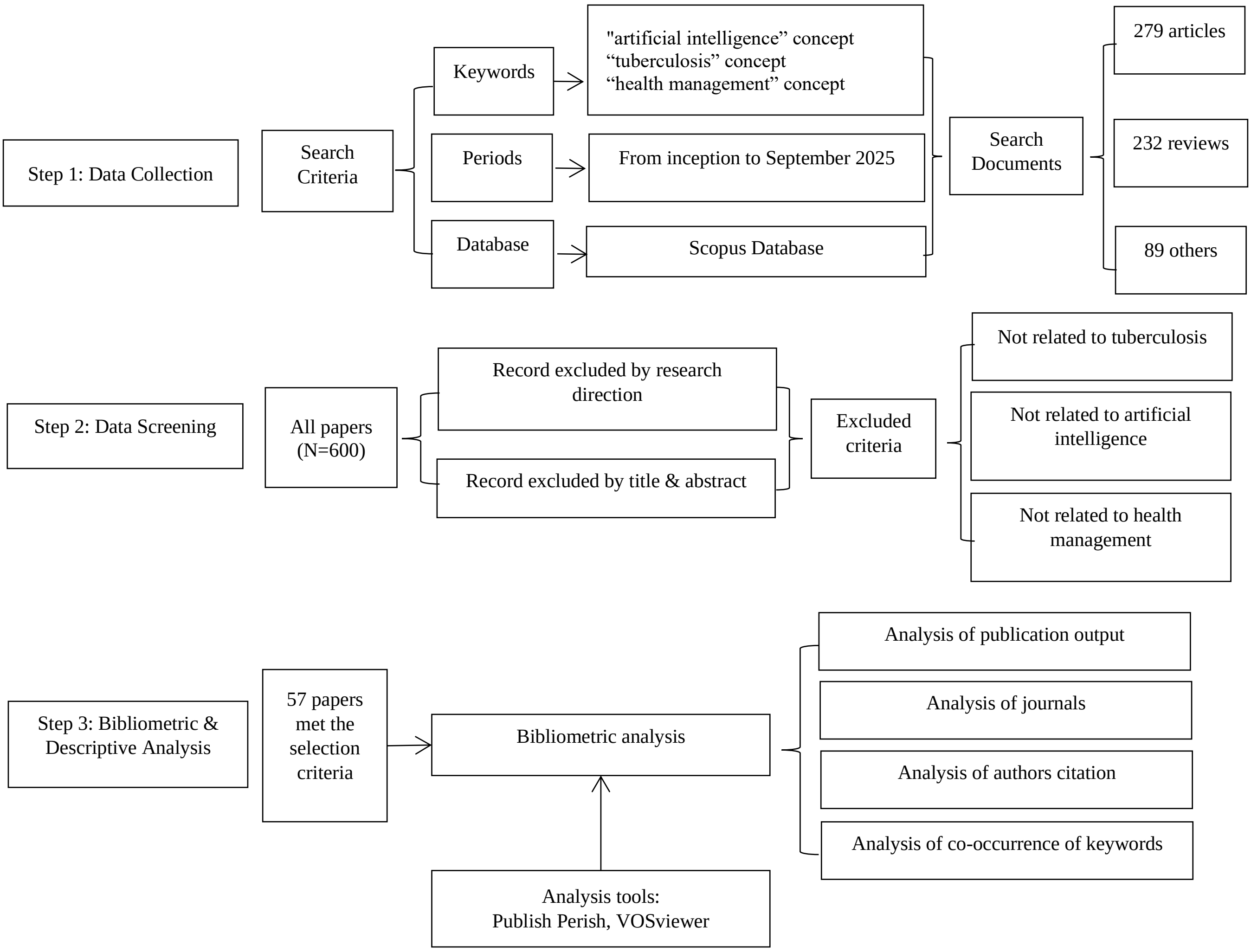

Figure 1. Flowchart of the literature-screening process and research framework

Keyword co-occurrence and thematic network mapping were conducted using VOSviewer. The parameter settings were configured as follows:

- Analysis Type: Co-occurrence analysis using Author and Index Keywords.
- Counting Method: Full counting method (where each co-occurrence link carries equal weight regardless of total keyword count per document).
- Threshold Settings: A minimum occurrence threshold of 3 was set for keyword inclusion, yielding 10 core keywords that formed 4 distinct thematic clusters.
- Layout and Clustering Parameters: Association strength was used as the normalization method, with a resolution parameter of 1.00 and a cluster density layout optimized for spatial separation.

VOSviewer, developed by the Centre for Science and Technology Studies at Leiden University, was then used to map and visualize bibliometric networks (van Eck & Waltman, 2010). The software is well suited for large datasets and was applied here to construct keyword co-occurrence networks. Through these visualizations, VOSviewer helped clarify dominant research themes, emerging clusters, and the intellectual structure of AI applications in TB **(Figure 1)**.

Ethical Consideration

This study relied entirely on publicly available bibliometric data and did not involve human participants; therefore, no ethical approval was required.

RESULTS AND DISCUSSION

Analysis of Publication Output

From an initial retrieval of 600 articles from the Scopus, a final set of 57 publications (9.50%) was included after data cleaning and eligibility screening. Table 1 illustrates the full screening workflow and the overall analytical framework, while **Figure 2** shows the yearly publication trends. Between 2017 and 2022, research activity was minimal, with fewer than five publications per year. The field began to gain traction in 2023, with annual output consistently exceeding 10 publications from 2023 to 2025. A sharp acceleration was in 2024, culminating in a peak of 21 publications.

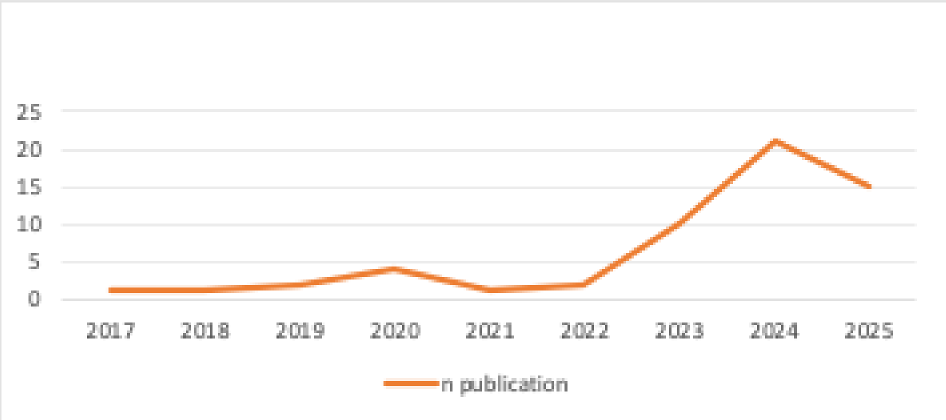

Figure 2. Number of publications Output

Analysis of Journals

Journal analysis helps identify the core publication outlets shaping the field. **Table 1** summarizes the top 10 journals ranked by publication volume. The Indian Journal of Tuberculosis recorded the highest output, contributing 3 articles (5.26% of all publications). Its strong impact factor reinforces its role as a leading source for research at the intersection of digital technology and health—an area directly aligned with AI applications in TB.

In terms of global citation influence (TGCS), the International Journal of Biomedical Imaging stood out, with TGCS values of 101, respectively, followed by the International Journal of Tuberculosis and Lung Disease. This highlights their broad international visibility and sustained impact, especially in digital health and AI-driven disease management.

When examining local citation influence within the dataset (TLCS), International Journal of Biomedical Imaging also showed notable contributions, scoring TLCS values of 101, followed by International Journal of Tuberculosis and Lung Disease with TLCS values of 11. These journals remain influential in shaping methodological and technological discussions relevant to AI-supported TB diagnostics and care **(Table 2)**.

Table 1. Top 10 Journal by number of Publication

Rank	Institution	Publications n (%)	TLCS	TGCS
1	Indian Journal of Tuberculosis	5.26 (3)	2	2
2	Communications in Computer and Information Science	3.51 (2)	0	0
3	2024 3rd International Conference for Innovation in Technology Inocon 2024	1.75 (1)	10	10
4	Global Virology III Virology in the 21st Century	1.75 (1)	0	0

5	Health and Technology	1.75 (1)	9	9
6	Indian Journal of Medical Research	1.75 (1)	0	0
7	Infection and Drug Resistance	1.75 (1)	3	3
8	Infectious Diseases Now	1.75 (1)	0	0
9	International Journal of Biomedical Imaging	1.75 (1)	101	101
10	International Journal of Tuberculosis and Lung Disease	1.75 (1)	11	11

Analysis of Authors Citation

Articles with strong citation impact have achieved visibility far beyond their original context. They are frequently referenced across countries, institutions, and research groups, indicating that the findings are robust, transferable, and valuable to the global TB community. These are the studies shaping policy discussions, informing AI model development, and providing the scientific foundation for future TB technologies.

Table 2 lists the top 10 most cited articles in the field. Authors from China - such as Fang et al. (2020), rank prominently, underscoring China's strong research activity and growing influence in AI-related tuberculosis work. Additionally, researchers across the world (Al Meslamani et al., 2024; Avanzato et al., 2024; Doshi et al., 2017; Liang et al., 2022; Ming et al., 2019; Qureshi et al., 2024; Sharma et al., 2020; Theodosiou & Read, 2023) are also actively advancing AI-driven TB studies, reflecting a global scientific momentum toward integrating machine learning and digital technologies into TB control. From all over the world, AI-based TB models are being developed, tested, and deployed to improve diagnostics, predict drug resistance, support treatment monitoring, and strengthen public-health decision-making. This widespread international engagement underscores one key reality that AI is no longer optional in TB management. It has become a critical tool for speeding up detection, optimizing treatment strategies, reducing transmission, and ultimately supporting global efforts to eliminate TB.

Despite the presence of these clusters, the table shows limited direct collaboration with one another, indicating that high-output contributors often work within separate, localized research networks rather than forming a single cohesive collaborative structure.

Table 2. Top 10 Author by number of Citation

Rank	Author	Cites
1	E.F. Fang	516
2	A.A. Theodosiou	152
3	A. Sharma	101
4	J. Haemmerli	67
5	S. Liang	40
6	R. Avanzato	28
7	A.Z. Al Meslamani	28
8	D. Ming	25
9	R. Doshi	22
10	H. Qureshi	22

Analysis of Keyword Co-occurrence and Network Topology

To move beyond basic descriptive counts, network parameters—including node degree, cluster size, and Total Link Strength (TLS)—were calculated using VOSviewer to capture the relational weight and structural centrality of key terms. TLS quantifies the total strength of co-occurrence links connecting a given keyword to all other keywords in the network. The constructed network comprises 10 core keywords meeting the minimum occurrence threshold, structured into 4 thematic clusters.

Cluster Sizes and Network Topology

- Cluster 1: Serves as the primary structural anchor of the network. The node *artificial intelligence* exhibited the highest centrality across the dataset, with 17 occurrences and a TLS of 28. It formed robust direct connections with *diagnosis* (10 occurrences, TLS = 20), *management* (8 occurrences, TLS = 16), and *role* (4 occurrences, TLS = 8). This high link density underscores that diagnostic model development remains the central hub around which the AI-TB literature revolves.
- Cluster 2: Captures clinical applications in infectious disease monitoring. The node *application* recorded 5 occurrences (TLS = 10), closely linked to *infectious disease* (4 occurrences, TLS = 8). Although smaller in node size, its cross-cluster linkages with Cluster 1 demonstrate an active migration toward applying AI models to drug-resistance mapping and epidemiological tracking.
- Cluster 3: Highlights technical machine-learning applications in screening. The term *tuberculosis* (10 occurrences, TLS = 18) acts as a critical bridge node connecting computational methodologies with operational terms like *treatment* (3 occurrences, TLS = 6).
- Cluster 4: Reflects health-system integration. It consists of *classification* (3 occurrences, TLS = 5) and *prevention* (3 occurrences, TLS = 5). Located on the structural periphery of the network map, this cluster indicates that while digital prevention and classification tools are emerging, they are not yet fully integrated into mainstream algorithmic research.

Temporal Overlay and Evolution of Keywords

A temporal overlay analysis of average publication years reveals a clear structural shift in research focus across three distinct phases:

- Early Phase: The literature was anchored by broad baseline terms like *tuberculosis* and binary *classification*, reflecting initial exploratory work focused primarily on standalone offline chest X-ray reading models.
- Expansion Phase: Centrality shifted rapidly toward *artificial intelligence* and *diagnosis*, driven by the maturation of deep-learning architectures and broader access to multi-center chest radiograph datasets.
- Emerging Frontier: The overlay map reveals that the most recent peripheral nodes are *management*, *prevention*, and *infectious disease*. This temporal shift confirms that the field is actively transitioning from basic diagnostic image automation toward multi-modal systems designed for adherence tracking, drug-resistance forecasting, and health-system management.

Figure 3. Visualization of Co-occurrence of Keywords Network

Table 3. Selected Terms and Cluster

Cluster Themes	**Keyword Node**	**Occurrences**	Total Link Strength (TLS)	Primary Linked Nodes
Cluster 1(Red): AI-assisted TB prediction	Artificial Intelligence	17	28	Diagnosis, Management, Tuberculosis
	Diagnosis	10	20	Artificial Intelligence, Role, Management
	Management	8	16	Artificial Intelligence, Diagnosis
	Role	4	8	Artificial Intelligence, Diagnosis
Cluster 2 (Green): AI for monitoring treatment responses and drug-resistant TB patterns	Application	5	10	Infectious Disease, Artificial Intelligence
	Infectious Disease	4	8	Application, Artificial Intelligence
Cluster 3 (Blue): Machine-learning models developed for TB screening	Treatment	3	18	Artificial Intelligence, Treatment
	Tuberculosis	10	6	Tuberculosis, Diagnosis
Cluster 3 (Yellow): Digital platforms and remote health technologies into TB management and disease prevention	classification	3	5	Prevention, Artificial Intelligence
	Prevention	3	5	Classification, Artificial Intelligence

DISCUSSION

The publication output trend shows that AI-related TB research is still an emerging field but is rapidly gaining traction. Of the initial 600 articles retrieved from Scopus, only 57 publications (9.50%) met the inclusion criteria, highlighting how niche and specialized this research area remains. Early activity was sparse, with fewer than five publications per year between 2017 and 2022, suggesting that AI applications in TB were still in the exploratory or experimental phase. The turning point came in 2023, where the annual output consistently exceeded ten articles. This growth accelerated sharply in 2024, culminating in the highest output of 21 publications. The surge mirrors a global shift toward integrating AI into infectious disease management, driven by better computational capacity, increasing availability of TB datasets, and strategic commitments by governments and global health agencies to modernize TB programs.

Journal analysis shows a relatively concentrated publication landscape. The *Indian Journal of Tuberculosis* emerged as the most productive outlet, reflecting its regional relevance in a high-burden setting and its alignment with digital health and AI-related content. Meanwhile, *International Journal of Biomedical Imaging* demonstrated the strongest global citation influence—highlighting that TB-AI work rooted in imaging, such as chest X-ray interpretation and radiographic pattern recognition, remains the most widely recognized and cited internationally. Its leading TLCS score reinforces how foundational imaging-focused AI studies are within this research domain. The contribution of journals further positions this field at the intersection of clinical TB management and computational innovation.

Author citation analysis reveals a geographically diverse pool of contributors with varying levels of collaboration. Several authors from China (Fang et al., 2020; Liang et al., 2022; Ming et al., 2019), rank prominently, underscoring China's strong research activity and growing influence in AI-related tuberculosis work. Additionally, researchers across the world (Al Meslamani et al., 2024; Avanzato et al., 2024; Doshi et al., 2017; Haemmerli et al., 2023; Qureshi et al., 2024; Sharma et al., 2020; Theodosiou & Read, 2023) et al., 2024) dominate the productivity rankings, reflecting the country's strong investment in biomedical AI, robust data infrastructure, and national priority to curb TB. Their outputs reflect a rapidly expanding global ecosystem where machine learning tools are being applied to TB diagnosis, drug resistance prediction, treatment adherence monitoring, epidemiological forecasting, and digital surveillance. This global spread underscores that AI-based TB research is no longer restricted to technologically advanced regions; it has penetrated high-burden and resource-limited settings where innovative TB solutions are urgently needed.

Yet, despite this growing international presence, collaboration remains fragmented. The most productive authors work largely within localized or institution-specific networks, with limited cross-collaboration between top contributors. This fragmentation may stem from data-sharing restrictions, differing national TB research agendas, and the uneven distribution of digital infrastructure across countries. Strengthening cross-border collaboration could accelerate methodological breakthroughs, improve dataset diversity, and enhance the external validity of AI models deployed in TB care.

Regarding to keywords, by analyzing keyword co-occurrence, this study shows that AI research in TB concentrates on four major areas: AI-assisted TB prediction, AI for monitoring treatment responses and drug-resistant TB patterns, machine-learning models developed for TB screening, and the embedded digital platforms and remote health technologies into TB management and disease prevention. The themes are, therefore, promising, leading the AI implementation into further era. For example, in TB diagnostics, AI models—especially deep learning applied to chest X-ray and CT images—have demonstrated strong capability in identifying pulmonary abnormalities that indicate active TB (Sharma et al., 2020). These systems can detect subtle radiographic patterns often missed in routine screening, enabling faster case identification and reducing diagnostic delays. Beyond imaging, machine-learning approaches have been used to analyze genomic data from *Mycobacterium tuberculosis* to predict drug-resistance profiles, supporting rapid and more precise selection of effective treatment regimens.

AI also enhances treatment monitoring (Avanzato et al., 2024). Models trained on clinical, radiologic, and laboratory data can predict treatment response trajectories, identify patients at high risk of treatment failure, and support early intervention. In community-based settings, AI-enabled mobile applications and digital adherence technologies help track medication intake, flag missed doses, and provide tailored reminders—tools that significantly improve adherence in TB management. Additionally, remote monitoring systems integrated with AI can detect early clinical deterioration or persistent symptoms, enabling timely follow-up and reducing the risk of severe outcomes(Liang et al., 2022).

Due to the development of AI's brain of machine learning, in recent years, it has gained strong traction in TB research, reflected by the increasing frequency of TB-related AI keywords in bibliometric analyses (Al Meslamani et al., 2024; Qureshi et al., 2024; Theodosiou & Read, 2023). This field has become a major hotspot as machine learning models continue to show clear advantages in TB detection, drug-resistance prediction, treatment outcome forecasting, and adherence monitoring. A central area of development is TB diagnosis. Machine learning and deep learning models have demonstrated high accuracy in interpreting chest X-ray and CT images, allowing automated detection of radiographic abnormalities linked to active TB (Sharma et al., 2020). Unlike conventional manual reading, these models can process large imaging datasets, recognize complex visual patterns, and provide rapid, consistent diagnostic support—particularly valuable in settings with limited radiology capacity (Theodosiou & Read, 2023).

Beyond imaging, machine learning also plays a key role in predicting drug resistance(Liang et al., 2022). By analyzing genomic sequences of *Mycobacterium tuberculosis,* machine-learning algorithms can identify mutation patterns associated with resistance to first-line and second-line drugs. This helps clinicians select effective regimens earlier, reducing delays associated with traditional culture-based drug susceptibility testing (Ming et al., 2019). Machine learning has also shown strong potential in personalizing TB treatment. Models trained on clinical indicators, imaging progression, laboratory results, and sociodemographic factors can predict the likelihood of treatment success, risk of relapse, or probability of developing severe disease (Al Meslamani et al., 2024). This enables tailored interventions for high-risk patients and more efficient allocation of healthcare resources.

In addition, machine learning supports remote monitoring and patient adherence management (Doshi et al., 2017). Digital adherence technologies—such as AI-powered mobile apps, video-observed therapy (VOT), and smart pillboxes—use predictive models to identify patients likely to miss doses, detect high-risk behavior patterns, and trigger targeted follow-up. These tools help maintain treatment continuity, a crucial factor in preventing drug resistance and treatment failure.

Although progress in AI applications for TB is substantial—particularly in imaging, drug-resistance prediction, and adherence monitoring—gaps remain. Many AI systems still lack large-scale clinical validation, and real-world performance varies across populations due to differences in imaging quality, comorbidities, and resource settings (Chen et al., 2023). Future research must prioritize multi-center clinical trials, long-term outcome evaluation, and equitable deployment strategies to ensure these technologies deliver reliable, scalable, and sustainable impact in global TB control.

Several challenges also persist. Many existing AI models show performance variability when applied across different populations, regions, or imaging conditions, highlighting issues with generalizability. Clinical validation is also still limited, as many AI algorithms remain confined to experimental datasets rather than real-world practice. Future work must prioritize robust model development, improved interpretability, and large, multi-country clinical trials to ensure safe, reliable deployment. Enhanced data sharing and standardized evaluation frameworks will also be essential to accelerate the translation of machine learning technologies into practical TB control strategies.

Overall, the research trends identified in this study align with and extend prior bibliometric evaluations of AI in infectious disease management. Consistent with broader bibliometric analyses of machine learning in tuberculosis, our findings confirm a post-2022 exponential growth trajectory in scientific output. Earlier bibliometric mapping by studies such as those analyzing general AI related TB applications revealed an over-concentration on basic computer-aided detection (CAD) and standalone chest X-ray classification. Our updated findings demonstrate partial continuity with this baseline, as diagnostic screening models remain a major thematic pillar.

Moreover, the identified keyword co-occurrence clusters provide a roadmap for the future landscape of AI-supported TB control: Clinical Practice (Clusters 1 & 3 - Diagnostic Triage & Screening): The strong centrality of terms such as *diagnosis*, *prediction*, and *machine learning* signifies a shift toward integrated clinical decision-support systems. In clinical workflows, deep learning models will increasingly serve as a first-line pre-screening filter to prioritize symptomatic patients for secondary molecular testing , drastically shortening time-to-treatment in high-volume clinics; Health Policy and Governance (Cluster 2 - Disease Surveillance & Monitoring): The clustering of *application* and *infectious disease* underscores the growing intersection between AI tools and public health surveillance. For policymakers, these clusters highlight the opportunity to integrate predictive analytics into national TB control programs (NTPs). To support this, health authorities must establish standardized regulatory frameworks for algorithm validation and data privacy; AI Implementation & Health System Integration (Cluster 4 - Digital Platforms & Prevention): The emergence of terms like *classification*, *prevention*, and digital health technologies points to real-world deployment challenges. Successful implementation hinges on moving algorithms from standalone local workstations to cloud- and mobile-enabled platforms. Integrating AI with digital adherence tools (such as video-observed therapy and smart pillboxes) allows remote monitoring of adherence behaviors, flagging high-risk patients for targeted field-worker intervention. Addressing infrastructure gaps—such as offline algorithmic functionality in low-resource environments—will determine whether these digital tools can be sustained in community health systems.

CONCLUSION AND SUGGESTION

This bibliometric analysis demonstrates that AI applications in TB management are rapidly expanding, transitioning from basic automated image classification toward complex, decision-support tools. However, these findings must be interpreted within certain methodological limitations, including database restriction to Scopus, exclusion of non-English and conference literature, and the inherent inability of quantitative citation metrics to fully reflect clinical utility or operational feasibility in real-world healthcare settings.

Despite these limitations, the thematic clusters identified offer crucial practical directions for advancing AI-supported TB control across three key stakeholder groups: for researchers, scientific efforts must pivot from redundant diagnostic image-classification studies toward neglected, high-impact fronts. Priorities should focus on developing multi-modal algorithms to predict drug resistance, monitor treatment adherence, and support long-term recovery trajectories. Regarding to clinicians, AI tools should be evaluated and implemented as clinical decision-support systems rather than standalone diagnostic replacements. For policymakers, undoubtedly, public health leaders must prioritize cross-border research collaborations and invest in digital infrastructure, particularly in high-burden, resource-limited settings. Standardized evaluation frameworks, ethical data-sharing protocols, and regulatory pathways are urgently needed to transition validated AI models from pilot initiatives to scalable, sustainable national TB programs.

STRENGTHS

This study provides a structured, data-driven overview of the global research landscape by combining publication trends, citation networks, and keyword clustering. Using multiple bibliometric tools strengthens reliability, while analyzing keyword patterns exposes underlying research priorities and blind spots. The approach gives a clear picture of how AI-TB research has evolved and where it needs to go.

LIMITATIONS

The analysis depends entirely on what is indexed in selected databases; any gaps in coverage affect the results. Citation counts favor older publications, which can distort the perceived impact of newer but potentially more innovative work. Keyword variations and inconsistent author terminology may also fragment thematic clustering. Lastly, bibliometric data cannot fully capture model performance, clinical relevance, or real-world feasibility—meaning the quantitative patterns must still be interpreted within a broader clinical context.

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CONFLICT OF INTEREST

The study received institutional support; however, the author declares no conflicts of interest and confirms that the funding body had no role in the design, analysis, or interpretation of the review.

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