AI solutions for TB Elimination

Defining the scope of AI solutions within NTEP

TRACETB

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Central TB Division, Ministry of Health & Family Welfare
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Purpose of the document

The NTEP (National TB Elimination Program) along with USAID aims to aid innovators and leverage emerging technologies such as artificial intelligence (AI) to accelerate tuberculosis elimination efforts. The NTEP has identified areas and articulated problems within the TB cascade of care that are AI-amenable. However, the NTEP is aware that this is a non-exhaustive list and is open to exploring new problem areas and solutions.

The purpose of this document is to motivate and invite individuals and organizations to develop AI-based solutions for TB. The conclusion section of the document describes the process for engaging with the NTEP and USAID on AI-based solutions.

As healthcare and technology are rapidly evolving, this document will be revised every year to reflect the most current technological advances, epidemiological changes, contextual information, and the burden of TB within the country, along with other factors.

Background

Digital health or “healthtech” is growing exponentially and technology is transforming the way healthcare is delivered. Higher smartphone usage, improved healthcare IT and infrastructure, and increased receptiveness for digital solutions have influenced the adoption of emerging technologies like artificial intelligence in healthcare.

While healthtech is flourishing in the private sector, it has not yet made a dent in large-scale government systems due to gaps that exist on both ends of the spectrum. Innovators and organizations have technical excellence and capabilities to build advanced solutions, but they often struggle with implementing them within the public health architecture. Moreover, public health systems are not always equipped with an institutional mechanism to assess and implement AI solutions. In parallel, for international funding agencies the potential impact areas of their investments may not be clear. Hence, it is critical to identify problem areas, articulate opportunities for solutions, ensure buy-in from all stakeholders and define processes for successful implementation in public systems.

Stakeholder	Value proposition
Innovators	Clearly defined problems that aligned with the government’s efforts.
NTEP	Acceleration of elimination efforts through improved decision-making, operational efficiency and process outcomes
Donors	Targeted investment opportunities and clear path to aiding government programmes.
Technical Partners	Design, deploy and adapt models for care at scale.

Abbreviations

Abbreviations	Full Form
ADR	Adverse Drug Reaction
AI	Artificial Intelligence
CT	Computed Tomography
CTD	Central TB Division
CXR	Chest X-Ray
HIV	Human Immunodeficiency Virus
ICT	Information and Communication Technology
LTBI	Latent TB Infection
LPA	Line Probe Assay
LFU	Loss to Follow Up
MDR-TB	Multidrug-Resistant Tuberculosis
ML	Machine Learning
MoHFW	Ministry of Health and Family Welfare
NSP	National Strategic Plan
NTEP	National Tuberculosis Elimination Program
SDG	Sustainable Development Goal
LPA	Line Probe Assay
TPT	Tuberculosis Preventative Treatment
UNHLM	United Nations High Level Meeting
USAID	United States Agency for International Development
WHO	World Health Organisation

Introduction

Tuberculosis (TB) is one of the top 10 causes of death worldwide and the leading cause of death from an infectious disease. Though our understanding of its causes and treatment began as far back as 1884, multiple challenges continue to persist in eliminating it completely even today[1].

TB is an airborne disease that can affect any individual. However, certain risk factors have been identified that make some people more susceptible to infection, such as undernutrition, smoking, alcohol abuse, HIV and diabetes. Overcrowding and poor ventilation increase the chances of TB spreading within a community[2].

Screening methods and diagnostic tests have been developed to detect TB. However, at the margins of society, access to tools that match the desired level of sensitivity remains a challenge. These challenges, coupled with wide systemic gaps, significantly hamper early detection of TB and identification of those who might be at risk.

Furthermore, existing tools for lowering risks and ensuring sustained prevention among very large populations have proven to be inadequate.

While the BCG vaccine prevents severe forms of TB among children, it cannot prevent disease transmission once a person is infected. Anti-TB medications are effective against TB, and a complete course of TB treatment can last anywhere from 6 months to a couple of years. The duration of treatment makes it difficult for patients to adhere to and complete the regime. ADR and lack of a support system further complicate the situation.

In addition to the medical issues mentioned above, there are a host of socio-cultural obstacles on the path to TB elimination. These include poor hygiene practices and care-seeking behaviour in communities, lack of awareness and stigma caused by discrimination towards TB patients. These hamper early detection and treatment completion, and also contribute to disease recurrence.

National TB Elimination Programme

Started in 1962, the National TB Elimination Programme (NTEP) is India's response to eliminating TB in the country. As the largest TB control program in the world the program has matured significantly over the last six decades. The Government of India has proposed 2025 as the target to achieve 80% reduction of TB incidence, five years ahead of the SDG timelines. To realize this ambition, the CTD, MoHFW GoI has been exploring the potential of innovative technological solutions to accelerate India's efforts.

In the last decade, technology has found applications in TB treatment, surveillance, program management and e-learning[3]. India has made great strides in integrating technology in the patient care cascade, and is also considered a major hub for digital health initiatives[4]. Expanding ICT support for TB elimination is included in the NSP.

To tackle the Covid-19 pandemic, public health systems had to explore alternative approaches, and digital technologies showed tremendous potential to support TB screening, diagnosis and treatment. This has also resulted in an increased demand for advanced data analytics, data-driven decision support, and AI.

All over India, tools that were earlier considered novelties have increasingly become commonplace, such as telemedicine, automated radiology, wearable health trackers, and chatbots. These serve various purposes such as automated transcription, assistance in routine medical tasks, and resource management. AI-based solutions can efficiently bring advanced, personalised expertise to the most far-flung patients and enable targeted, patient-centered healthcare delivery.

[1] India Annual TB report
[2] CDC - Risk factors
[3] Tuberculosis control, and the where and why of artificial intelligence
[4] Use of Digital Technology to Enhance Tuberculosis Control: Scoping Review

Methodology for identifying use cases

The aim of this document is to identify potential areas for AI-based intervention. The TB cascade of care was first analyzed for existing problem areas, which were then broken down into specific problem statements, and these were probed for AI-amenability.

Process overview: Analyzing the cascade of care

1. Desk research and analysis
2. Interviews with national and global experts in healthcare and AI
3. Brainstorming workshops with the NTEP, USAID, WHO and Wadhwani AI teams
4. Validation of ideas with technical stakeholders

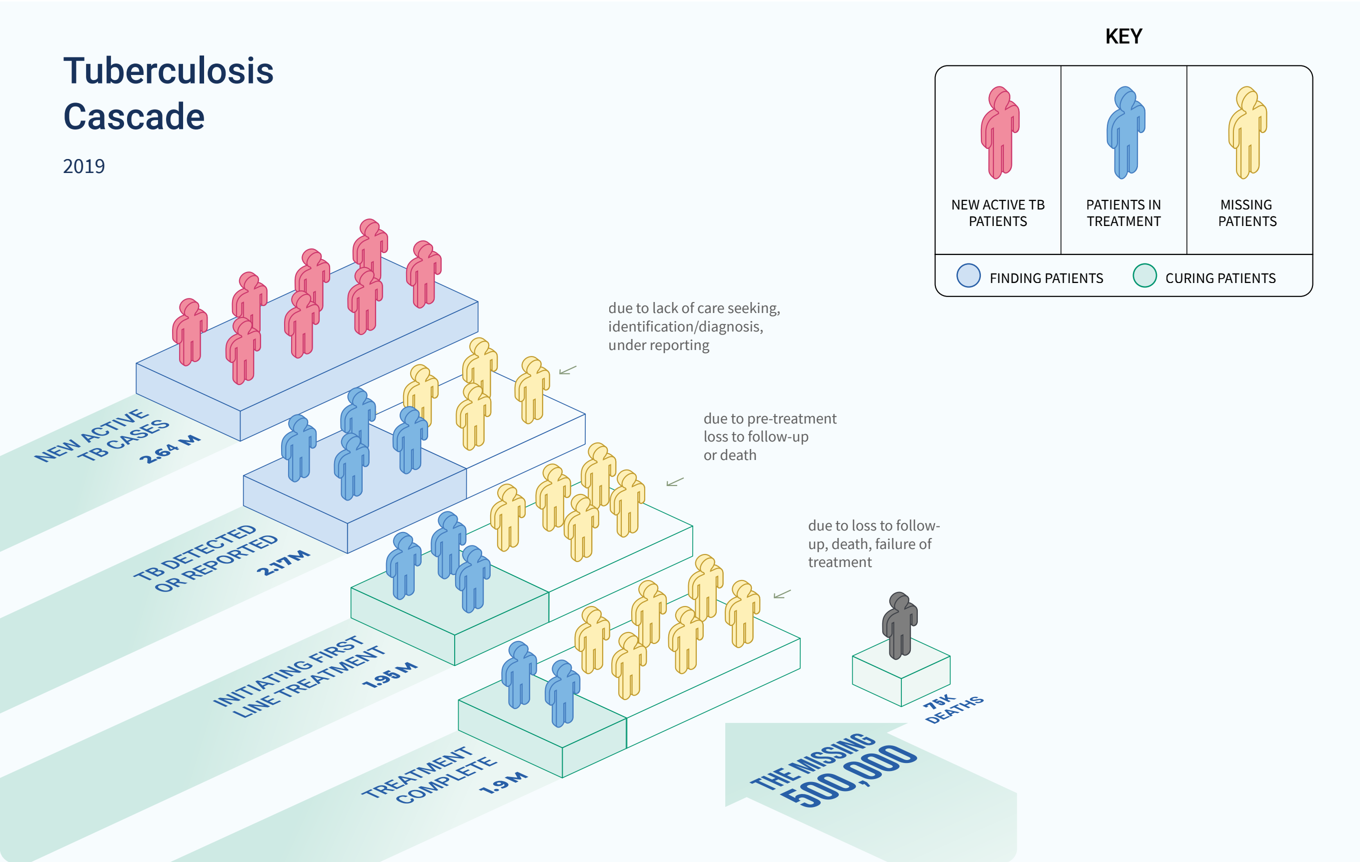


Exhibit 1: Identifying causes and number of dropouts at various stages in the TB care cascade.
Source: Global TB Report 2020; India TB Report 2020

Proposed framework for assessing AI-amenability

Defining the problem domain is the first step in assessing AI amenability. This allows us to drill down into specific problems that can be solved using AI/ML. While specific problems are formulated, critical assumptions and assertions must be identified and documented. In addition, the data requirements, metrics to optimize the model and the metrics used to evaluate the quality of the solution should also be defined.

Developing an AI solution is an iterative process. After building an initial version of the solution, the need for further data collection and analysis should be considered. Various challenges, including technical and programmatic, will be exposed after initial experimentation, and therefore requires a collaborative approach between diverse teams. Finally, the output of using this framework should be a clearly documented technical problem with specifications on type of data required and success metrics. This document must be agreed and signed off by team leads from all disciplines involved in the decision-making progress.

In this framework, clarity on problem definition does not always mean a quantitative understanding of the amount of data required to solve the problem, or a numerical value a certain metric should take to result in impact. Often, these will be unknown until initial model experimentation is completed and some on-ground experience is gained. In case a certain numerical value is crucial for impact, the rationale for this value should be supplied as a part of the problem definition. For example, in the case of detecting TB through automated X-ray analysis, the accuracy threshold that the AI should aim for can be based on existing metrics of human expert (radiologist) accuracy. The AI technology should therefore attempt to match or exceed this accuracy. In the case of predicting adherence on the other hand, the relevant accuracy metric as well as its numerical value may be less clear because corresponding manual baselines may not exist. In such cases, clarity is only obtained after some experimentation in building AI models and assessing interventions on the ground.

The following are some of the important aspects of the problem definition and AI-amenability assessment phase.

Infer the Right Outcome Variables	In the early stages of a project, and even at the proposal stage, it is important to cast the problem in a form that AI can tackle and select the right set of outcomes to be inferred or predicted using the AI to obtain an impactful outcome.
Heuristics vs ML	As rigorously as possible, the proposed project should evaluate whether AI/ML is really necessary to solve the problem, or whether simple rules,heuristics, or ground level manual interventions will suffice. Some of the considerations that are involved are issues of scale, accuracy, automation, and the discovery of hidden correlations.
Backward vs. Forward Thinking	For concrete AI tech that will be deployed and used at scale, it is important that the proposed project concretely addresses the conception of the deployed solution, its potential strengths and limitations, and then works backwards from there to define the problem and data needs accordingly.
Metrics	The metric of success of the AI deployment is intimately tied to the problem definition itself. Changing the metric can result in a completely different problem. The project should ideally identify one or more simple, interpretable metrics that nevertheless reflect the ground realities. Some of these metrics may be more relevant to the long-term success of the project, e.g., reduction in missing TB cases over time, but are difficult for the AI to optimize. The AI optimization may instead choose to operate on short-term proxies, such as the accuracy of TB detection.
Baselines	The project should aim to identify, wherever possible, a baseline or default solution to the problem that is already in use or obvious to use. The AI modeling method should aim to significantly improve this baseline.

This report identifies various problem areas that can be potentially addressed by AI solutions. However, it is important to acknowledge that most of the problem ideas are potential ideas that, at this point, exist at a conceptual stage.. This framework above is proposed to assess problems in-depth for AI amenability and lay down factors that should be considered while working on and designing the solutions.

Potential AI Use Cases

Identified problem areas and potential use cases were classified into four major categories based on the four pillars of the NTEP's NSP:

Prevent the emergence of TB in the populations.

Detect all DS-TB and DR-TB cases early. Find out all missing cases, especially undiagnosed patients in high-risk populations. Reach out to TB patients seeking care from the private sector.

Treat by maintaining consistent quality of care, patient-centred systems and social support. Initiate and sustain all patients on appropriate anti-TB treatment at the earliest and ensure completion of treatment with relapse free post-treatment survival.

Build enabling policies, empowered institutions and human resources with enhanced capacities.

Overview

This document contains a non-exhaustive set of use cases for AI/ML as of June 2021. The NTEP is open to collaborating with stakeholders to develop additional solutions that can contribute towards TB elimination.

Prevent	Detect	Treat	Build
1. Identify high-risk areas or populations for LTBI	1. Examining chest X-rays	1. Predict initial loss to follow up and treatment adherence	1. Decision support and programme management
2. Automated skin test reading	2. Targeted case-finding	2. Predict TB recurrence	2. Drug supply chain management
3. Treatment adherence of LTBI	3. Cough- and voice-based screening	3. Personalized care via chatbots	3. Healthcare provider engagement
	4. Reading LPA test results		4. Communication and behaviour change management
			5. Improve data quality

Note: Additional use cases are listed at the end of the document.

Prevent

At the UNHLM on TB in 2018, world leaders committed to providing preventive therapy to at least 30 million people by 2022[5], based on individual incidence estimates and projections for each country taken from WHO data[6]. Among all interventions, preventive treatment for TB is a global priority.

From producing effective vaccines, to employing measures that control airborne infection and reduce environmental risk, successful prevention of TB infection and transmission can significantly reduce a public system's burden.

Identifying high-risk areas for LTBI

Background

Individuals with Latent TB Infection or LTBI do not feel sick and may never show any symptoms. To prevent the TB bacteria from becoming active, TB preventive treatment or TPT is prescribed. Around 23% or around 1.7 billion[7] of the global population is estimated to have LTBI. In India, the estimate is 35-40%[8] of the population, of these, 5-10% might have weaker immunity are considered vulnerable to developing active TB.

Problem & Challenges

Since people do not exhibit symptoms they often do not seek care, which makes it difficult to identify whom to test for LTBI. Testing and treating a large section of the population is challenging and has limited the possibility of programmatic interventions. Therefore, a targeted approach is required.

[5] The Growing Importance of Tuberculosis Preventive Therapy and How Research and Innovation Can Enhance Its Implementation on the Ground
[6] StopTB global advocacy
[7] Global prevalence of Latent TB
[8] WHO Global TB report 2020

Opportunity

AI can help identify locations that are more vulnerable and therefore are in greater need of interventions. Based on a set of input parameters, a potential AI solution can predict the risk of LTBI cases turning into active TB, and categorize groups of people into high, medium and low priority. This would help relevant local authorities create targeted plans for action at the district and sub-district level. The proposed AI solution would analyse data on the specific indicators used to determine which LTBI may become active TB disease.

At the population level, a high priority label might result from a high prevalence of HIV and other immunocompromised conditions, greater ratio of healthcare workers, prison inmates and homeless people. Similarly, a low priority district would indicate greater prevalence of undernutrition, diabetes, and smokers. Populations can be further divided into subgroups based on demographic variables such as age, sex, education, migration background and ethnicity, marital status, employment status and income for better targetting. The expected output can be a heat map indicating various priority levels across a region.

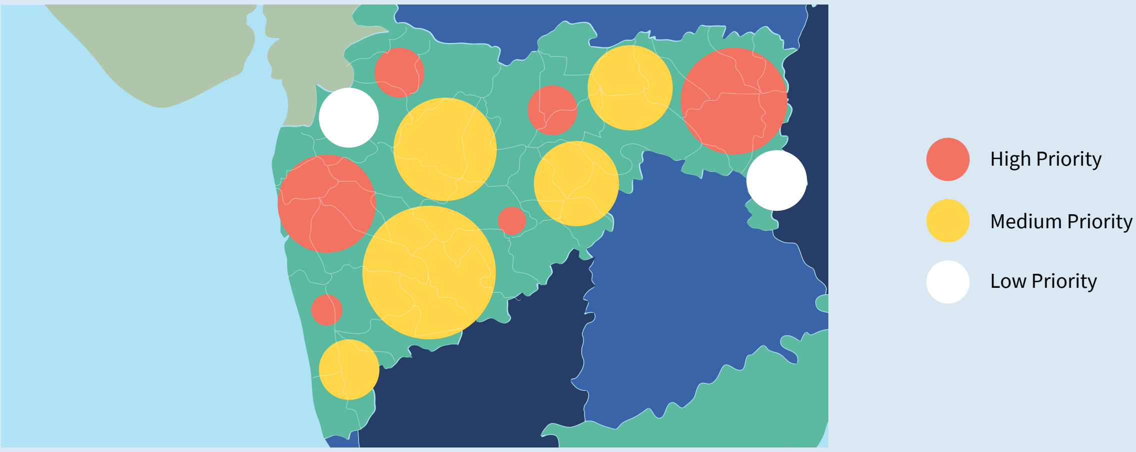


Exhibit 2: Identifying causes and number of dropouts at various stages in the TB care cascade.

Potential users

State TB Officers (STOs) and District TB Officers (DTOs) will use the predictions to plan programmatic interventions. At the central level in NTEP, the solution will help the CTD technical head, senior program managers from the WHO and relevant consultants better allocate appropriate resources.

Automated LTBI skin test reading

Background

The WHO recommends that either a Tuberculin skin test (TST) or Interferon Gamma Release Assay (IGRA) test[9] can be used to detect LTBI. New skin tests[10] are currently being developed that will be far superior in terms of accuracy, which could replace TST. However these tests will still require manual reading and interpretation.

Problem & Challenges

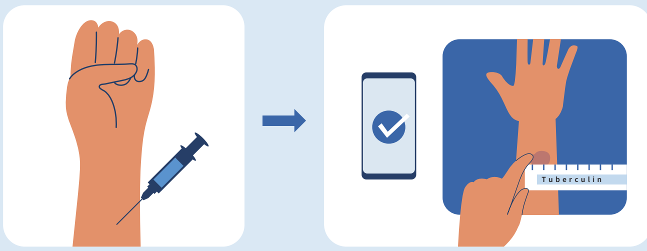
Skin tests are read between 48-72 hours after they are administered and are interpreted by well-trained health workers, who look for any presence of induration on the skin. Interpretation is thus based on the examining health worker's skill and experience, which can lead to inconsistent results[11,12]. To further increase the complexity, there tends to be a great deal of variation in indurations across different populations. In addition to challenges faced in testing procedure and interpretation, a patient is required to travel to a health facility for 2 separate visits, which can add to their financial burden. Currently, skin tests are used only to assist in pediatric TB diagnosis, but are expected to be widely used among adults in the near future. Since LTBI treatment is a priority

Opportunity

AI is a useful tool for automating repetitive processes and has proven to be at par with highly skilled medical professionals in analysing image-based data such as photos and videos. A computer vision solution can enable more accurate interpretation of skin test indurations. The patient or healthcare provider can take a photograph of the skin reaction on a smartphone, which can be processed by the AI algorithm directly on the same device to generate a recommendation.

This proposed AI solution can lower chances for human error and delay in obtaining results, as well as reduce the workload of health workers, thereby assisting the health system in scaling up LTBI evaluation in spite of limited skilled manpower.

The system can then turn its focus towards improved human interaction to ensure better follow ups and contact tracing, so as to lower dropout numbers.



1 2

Exhibit 3: A sample of the induration and interpretation of the skin test to determine the result for latent TB infection.

Potential users

A person who is tested with a skin test can take picture/s and send them to the health care worker or an application like Arogya Sathi can be provided to patients who are given skin test. The health workers and doctors will use reading and interpretation of AI solution for making decisions on treatment of LTBI.

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[9] WHO report
[10] https://www.thelancet.com/journals/lanres/article/PIIS2213-2600(17)30012-7/fulltext
[11] Sensitivity, specificity and predictive value of diagnostic tests
[12] View of Mantoux test

Detect

Early detection of both LTBI and active TB cases in a community is critical to cut the chain of transmission. Globally, 2.9 million TB cases are missing (gap between estimated cases and newly diagnosed cases) due to either underreporting of diagnosed cases or underdiagnosis[13].

Automated reading of chest X-Rays

Background

WHO indicates that an ideal TB triage test should require minimum training and have no requirement for sputum collection. The test should be fast, robust, portable, easy to maintain and affordable. Put simply, it should be accessible for both patients and health workers. Furthermore, it should have a minimum sensitivity of 90% in comparison with the confirmatory test, and a corresponding minimum specificity of 70%. CXR is a valuable triage test used by clinicians to diagnose TB early[14], and therefore its adoption has been growing. After the CXR is analysed, patients are referred for microbiological tests to confirm the diagnosis. Though the clinician may be able to diagnose a person based on their acumen, experience, and patient condition in certain cases, CXR is an important step for validation.

Problem & Challenges

CXR is a sensitive tool to detect pulmonary TB, however reading X-rays does require the medical expertise of a trained radiologist. This poses a challenge in low-resource, high-burden settings, and limits adoption. General practitioners lack the specialized training and there is a risk of cases being missed or delays in diagnosis.

[13] Global TB report 2020
[14] The long and winding road of chest radiography for tuberculosis detection

Opportunity

To supplement a shortage of radiologists or specialists in underserved communities, automated or AI-enabled reading of CXRs can bridge the expertise gap. AI solutions trained on millions of CXRs are already in development that can interpret CXRs, catch TB abnormalities and assign an abnormality score. This can help the healthcare provider decide which patients should be referred for microbiological testing to confirm the diagnosis.

Potential data inputs can include digital CXR images, patient medical history, clinical information and other supporting information on education, location, and socio-economic status. Outputs might be a classification of whether or not the CXR is indicative of TB. Additionally, the AI tool can generate a risk score to indicate a high or low probability of the individual being infected with TB, which could in turn help clinicians make appropriate decisions on further testing and treatment.

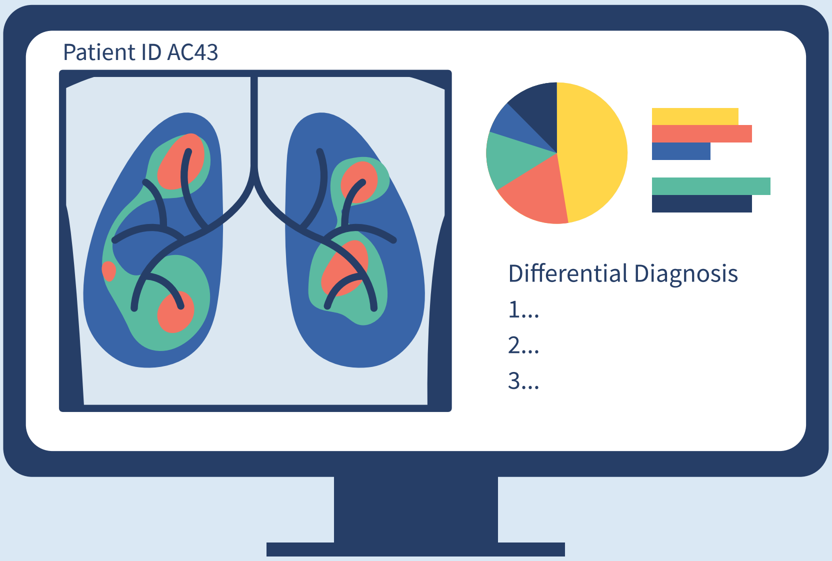


Exhibit 4 : An example of the CAD4TB system developed by Delft. It uses AI to interpret digital chest x-rays and provide a risk score which enables the care provider to refer patients accordingly.

Potential users

Health workers or clinicians at hospitals, community health centres or mobile health vans. In the absence of a doctor, an individual can upload their CXR through a photo. The AI solution can provide a preliminary risk score that helps them take necessary action such as a confirmatory test.

Targeted case finding

Background

Active case finding (ACF) is one of the most widely used strategies for identifying TB in high-risk populations, particularly where individuals may not proactively seek out diagnosis or visit a health facility. It involves systematic screening, referral for diagnosis confirmation followed by appropriate treatment enrolment. ACF is conducted on-ground, and often includes door-to-door screening, similar to 'contact tracing' conducted during the Covid-19 pandemic. It is a methodical, provider-initiated effort where success depends on the screening modality, characteristics of the targeted population, and strong links between diagnostic and treatment facilities.

Such efforts can result in early identification of cases, thereby reducing the potential severity of illness while also curbing transmission. ACF has been adopted by the NTEP as a way to find missing cases in at-risk populations.

Problem & Challenges

A low yield of cases is one of the biggest challenges for ACF. In 2020, NTEP screened 20% of the population with an NNS (Numbers Needed to Screen) value of 4400 to detect one case of TB[15] . Though ACF is a targeted approach, the NNS observed in India is higher compared to other high-burden countries[16]. The existing system also does not allow for refinement of the screening strategy in real time, as patients are screened.

Opportunity

AI has the capacity to learn large, complex datasets and provide actionable insights. In the case of ACF, it can help improve detection rates and optimize allocation of resources. Identifying missed hotspots and dark spots can guide the NTEP towards the missing active TB cases.

Potential inputs for identifying populations for ACF can be NTEP Nikshay data, satellite maps and information on private sector drug sales[17]. This could be supported by data on prevalence of factors such as HIV, diabetes, undernutrition, smoking, alcohol abuse, indoor air pollution, immunocompromised conditions, data on occupation, workplaces (health care settings, mining), socio-economic status, density of population, residential institutes, high TB prevalence geographies, access to health facilities, and factors indicating the strength of health systems. The expected outcome can be a heatmap at a district or sub-district level which highlights priority areas for ACF interventions along with recommended frequency.

Exhibit 5 :A potential AI-based solution that helps improve active case finding by identifying at-risk geographies.

Potential users

DTOs and STOs that plan and implement ACF interventions.

[17] WHO TB screening guidelines

Cough and voice-based screening

Background

During symptomatic screening, the first step in the pathway to TB diagnosis, individuals are asked about the presence of key symptoms that are indicative of the disease. One of the main priorities for TB diagnostic research internationally is a rapid, non-invasive triage test for TB screening , that is capable of detecting more patients and reducing the burden of expensive diagnostic tests.

Problem & Challenges

The process of collecting symptomatic information is entirely manual and requires close human interaction between health workers and the general population. It can be diluted by personal biases at both ends – worker and potential patient – and thus yields subpar outcomes, especially in large-scale field-level screening. There is also room for human error in reporting and interpretation, which necessitates an inexpensive, unbiased procedure that can be easily scaled widely. A triage test with a high sensitivity can be used to target individuals that are more likely to test positive on confirmatory microbiological testing.

Opportunity

AI tools like deep learning have a demonstrated ability to identify features in audio signals[19]. A persistent cough that lasts for more than 2 weeks is the most dominant symptom of pulmonary TB and can be used for screening purposes. It is hypothesized that the cough sounds of a pulmonary TB patient may carry a unique signature that may not be easily detectable by human ears. Even in the absence of persistent cough, AI can potentially help discern TB signals in cough sounds. Hence, if an AI solution can learn features of cough sounds that are indicative of pulmonary TB, it can also classify individuals into healthy and TB-probable patients in real-time.

This can then be used as a screening tool to triage patients for confirmatory tests and benefit the system by reducing workload on health workers. It can also enable independent self-screening.

A large dataset of recorded cough sounds of TB positive and healthy patients is required to develop such a solution, along with additional data such as demographic information, medical history on pre-existing health conditions. The expected outcome can be a risk score for each patient that will help decide whether to refer them for a confirmatory test.

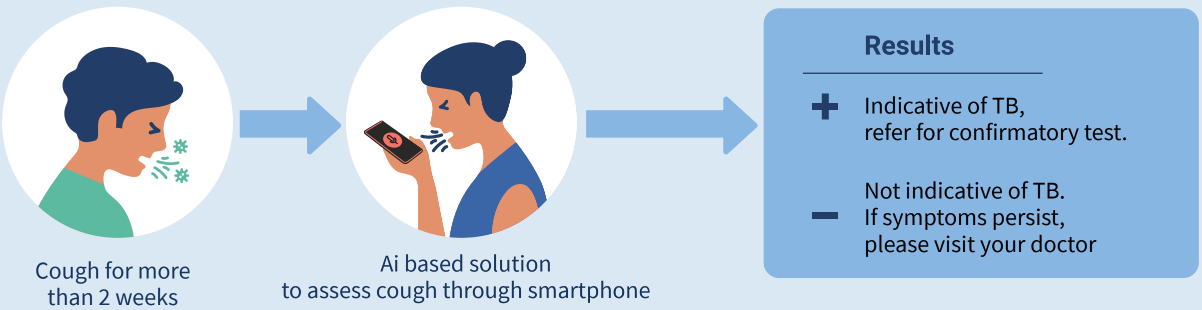


Exhibit 6 : Cough sounds can be analyzed to determine the probability of active TB disease, and potentially enable self-testing.

Potential users

Frontline healthcare workers and the patients themselves. The solution can be integrated with the NTEP's Aarogya Saathi app and Nikshay digital system to trigger appropriate action and help reduce staff workload.

[19] AI and cough sounds in COVID-19

Reading of LPA test result

Background

When the TB bacteria develops resistance to the first line of treatment comprising the two most powerful drugs, isoniazid and rifampin, this is referred to as multidrug-resistant tuberculosis or MDR-TB. Half a million people annually fall ill with MDR-TB worldwide , posing a formidable challenge to health systems as a result of prolonged illness, greater drug-related side effects and longer duration of treatment and.

In 2011, the Line Probe Assay (LPA) test was introduced to diagnose drug resistance among newly diagnosed TB cases. LPA is a rapid molecular diagnostic technique that reduces the turnaround time of results from a minimum of 3 months (as is the case of culture and drug-susceptibility methods) to only 3 days.

It is a strip-based technology developed to test resistance to isoniazid and a subset of rifampicin-resistant patients get tested for second line anti-TB drugs. In India, LPA tests are available at 64 labs in the public sector and the country tests 4 lakh TB patients annually .

Problem & Challenges

The LPA test involves DNA extraction, multiplex PCR amplification, and reverse hybridization to obtain results. At present, reading, interpretation and transcription are manual processes, which creates scope for error, reduced accuracy and delay in delivering results. Given the large volume of cases and limited human resources, these issues can proliferate.

Opportunity

AI-enabled reading and interpretation of LPA strips can help the NTEP improve both efficiency and accuracy of test results. The solution can be integrated with Nikshay, the programme's digital information system and provide real-time updates on case prevalence at state and district levels. This can help with early diagnosis and referral for appropriate treatment of DR-TB patients.

The AI model learns a large, diverse dataset of LPA strip images that enables it to discern subtle variations indicating different mutations. Other inputs can include clinical information, medical history, as well as demographic and contextual information. The expected outcome can be a positive or negative test result, which is logged into Nikshay and triggers necessary responses, including notifying affected patients.

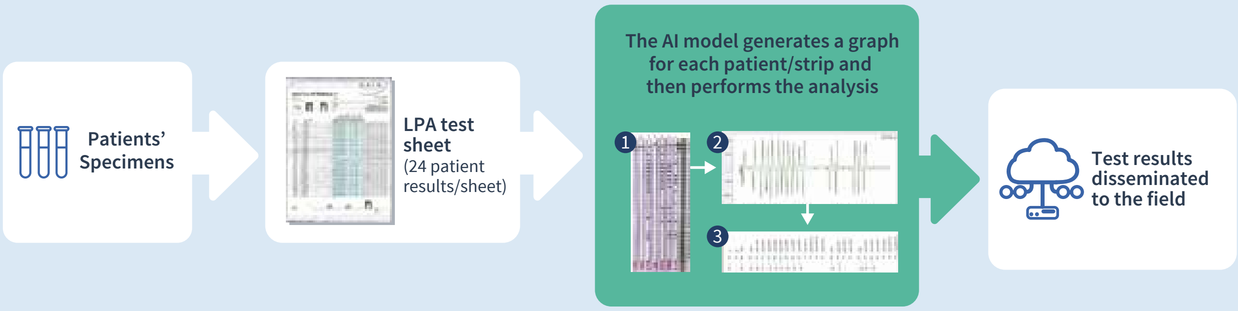


Exhibit 7 : The current manual interpretation of LPA strips can be replaced with an AI-enabled, app-based system.

Potential users

Lab technicians and microbiologists at LPA labs.

[20] WHO - Tackling DR-TB crisis
[21] Noncommercial culture and drug-susceptibility testing methods for screening patients at risk for multidrug- resistant tuberculosis
[22] India TB report 2019

Treat

TB patients have to overcome many hurdles, starting with the extended duration of treatment, ADRs and limited institutional support, while also dealing with discrimination and ignorance about the disease. In 2019, the treatment success rate for newly enrolled patients was 85%[23] . The remaining 15% either died, were lost to follow up or had a failed treatment regimen. Early diagnosis and successful treatment of TB patients are crucial to prevent prolonged illness, death, drug resistance and most importantly controlling community transmission.

Predict loss to follow up and treatment adherence

Background

The treatment for drug-susceptible TB lasts a minimum of six months, whereas for drug-resistant TB, it can last 24 months or more. Adhering to the treatment regimen can be particularly challenging: drop-offs, also known as Lost to Follow Up or LFU[24] are common. Poor adherence is the principal cause for treatment failure and increased risk of death[25]. In countries like India, LFU accounts for 3% to 17% of TB patients in treatment[26]. This variation is observed at a district to district level throughout the country.

Problem & Challenges

Timely action and additional support can significantly reduce LFU, however identifying patients at various stages of the TB cascade of care – starting from initiation of treatment – who might be at risk of dropping off, is difficult. At present the approach tends to be reactive, whereas a highly proactive one is the need of the hour. LFUs are often caught too late due to limited contact between the health system (via care providers) and patients. There is also presently no way to prioritize at-risk patients.

[23] India TB Report 2019
[24] https://tbcindia.gov.in/WriteReadData/NTEPTrainingModules1to4.pdf
[25] Challenges in tuberculosis drug research and development
[26] Barriers to treatment adherence of tuberculosis patients: A qualitative study in West Bengal, India

Opportunity

AI-enabled stratification of TB patients based on their risk of LFU can help health staff make proactive decisions and provide differentiated care. Such stratification should be available throughout the course of treatment, thanks to a strong data pipeline that collects a patient's adherence data, clinical and demographic information, as well as any other publicly available contextual data on population, health system and socio-economic factors.

The expected outputs can be -

• A lack-of-adherence risk score or category assigned to patients at treatment initiation time.
• A prioritized list of patients for additional follow-up, based on the risk of non-compliance.
• Missed notifications catalogued to predict the probability of non-adherence.
• An alerting mechanism built on top of an existing framework for adherence management.

LFU prediction could be accompanied by prediction of multiple possible outcomes of TB treatment. This can help improve treatment outcomes of TB patients overall. Additional input parameters can be added to increase prediction accuracy for mortality and treatment failure.

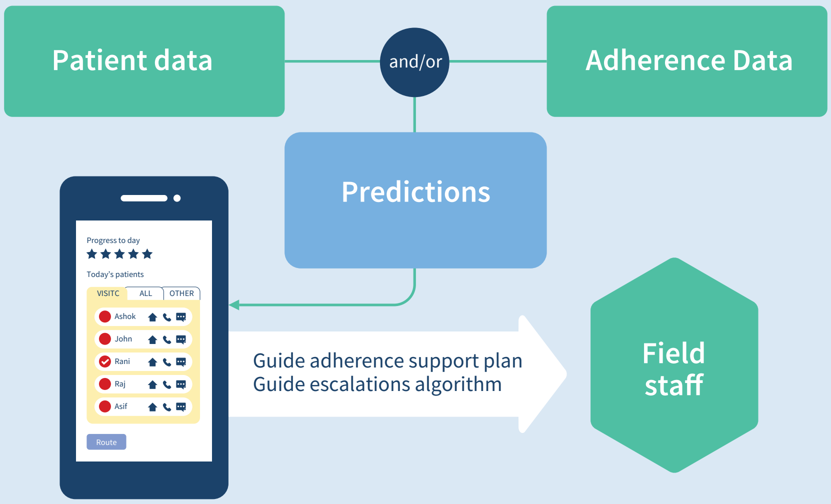


Exhibit 8: A sample workflow of an AI-based predictive algorithm that can help the system prioritize patients and improve the lost-to-follow up cases.

Potential users

Health workers who engage with patients for treatment support. A system of task lists and alerts can be created for the health worker to facilitate timely intervention.

Predicting TB recurrence

Background

Individuals who have completed treatment remain at elevated risk of TB recurrence due to either relapse or reinfection. Treatment outcomes are worse for recurrent patients than for first-time patients, with greater risks of LFU and death[27]. In India, the rate of disease recurrence among TB patients is ~10% within 2 years of successful treatment[28]. To identify these patients early, a post-treatment follow up strategy has been prescribed under the NTEP.

Problem & Challenges

Uptake for post-treatment follow up has been low across the country due to various challenges in implementing the strategy. TB patients may not show symptoms after successfully completing treatment and therefore don't seek additional testing. Healthcare providers need to actively contact every patient who has completed treatment within 2 years. However, this level of outreach to such a large group and after a significant gap of time can have mixed success.

Opportunity

An AI solution which scores patients based on predicted risk of recurrence. High-risk patients can be targeted for screening and diagnostic evaluation. Potential inputs for this solution can be clinical, demographic, comorbidity data, treatment outcome, and other contextual data.

Potential users

Health workers and district programme managers can use the tool to implement post-treatment follow up more efficiently.

[27] Risk factors for recurrent tuberculosis after successful treatment in a high burden setting: a cohort study

[28] Recurrence of tuberculosis among newly diagnosed sputum positive pulmonary tuberculosis patients treated under the Revised National Tuberculosis Control Programme, India: A multi-centric prospective study

Chatbot-aided personalized care

Background

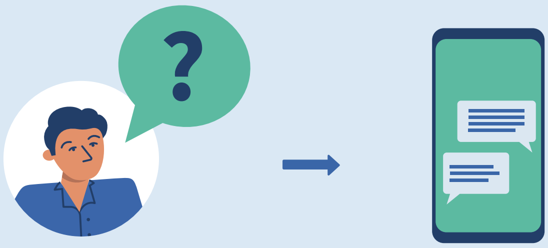
TB programmes globally are working to become more patient-centric through personalized care. To ensure effective delivery, regular engagement with patients, obtaining their feedback and providing timely response and remedial action are essential. NTEP has rolled out the TB Aarogya Sathi mobile application to promote TB awareness among patients and the general public, as well as to provide information about the nearest diagnostic and treatment centres and a screening tool to assess risk of infection. Other features include a BMI Calculator, nutritional advice and counseling. For patients registered under the NTEP the app serves as a portal to access digital health records; self-monitor testing, treatment and adherence; track the benefit amount paid under various incentive schemes; connect with a healthcare provider and request a teleconsultation.

Problem & Challenges

A robust platform that engages with patients directly must be capable of providing them with comprehensive and highly personalized real-time assistance. Responding to the large number of individual requests would require significant human resources and infrastructure, especially given the scale of the TB public health programme. It would prove unfeasible and unsustainable in the long-term.

Opportunity

Medical chatbots can be configured for TB. These AI chatbots can be programmed with vast amounts of information on all aspects of effective treatment management, and can be trained to provide locations of nearby care facilities, send reminders and follow up with patients. Additionally, they can respond to patients' most frequently asked questions. The potential inputs can include questions and queries from TB patients on medical care, help they need during the course of treatment – be it medical or non-medical, social support benefits offered by the programme and more. The chatbots would also need to be trained in regional languages so that the information is accessible to wider audiences. This would reduce the burden on health workers and providers, and enable them to give additional support to high-risk patients.



Patient queries regarding diagnosis, treatment, drug reactions, or counselling, etc.

AI-based chatbot for instant query resolution and referral

Can be integrated into
- TB Aarogya Sathi app.
- instant messenger applications like WhatsApp and Telegram.

Other features
- Patient feedback on services.
- Connecr with doctors for teleconsultation.
- Connect with peer supporters.

Exhibit 9 : An overview of the capabilities of the AI-enabled chatbot for patient care.

Potential users

TB patients and citizens who seek information on TB.

Build

A systems view is critical to fundamentally transform the way that TB care is provided, ensure the long-term viability of AI-based solutions, and eventually eliminate the disease altogether. This requires improving operational efficiencies, setting up enabling mechanisms and offering stakeholders a range of useful and easily implementable tools. Many of these AI tools and solutions already exist in other industries and health programmes, and can be adapted for the NTEP.

Decision support & programme management

Background

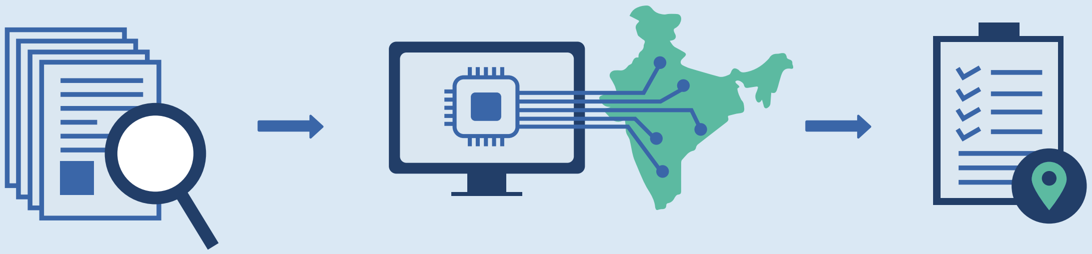
Resource planning for TB follows a certain set of standard practices. The NTEP conducts gap analysis, prioritizes needs, and allocates resources based on demand. However, in the absence of real-time data to guide decision-making, these processes can become inefficient and driven by personal inclinations, as opposed to verified on-ground needs.

Problem & Challenges

Programme units are allocated resources based on pre-decided norms. It is important to reframe allocations in response to shifting resource requirements to improve operational efficiency.

Opportunity

An AI solution that can forecast unit-level requirements and help prioritize resources to program managers at the central, state, and district offices. Potential inputs can be details on state and district demographics, geographical features, health systems, socio-economic and development indicators, determinants of disease, availability of human resources, and the pattern and distribution of disease. The AI solution will stratify districts and states based on the score generated by the algorithm to guide programme managers on resource planning.



Collating experiences and latest imformation from the field to feed the AI solution.

AI algorithm predicts the resource allocation required across geographies and rank orders them

Customized plans for each geography are generated for the program.

Exhibit 10 : An AI based decision support system built on various datasets including human experience, can create customized plans for specific geographies.

Potential users

Health workers and programme managers of the district can use the tool to implement post treatment follow up.

Drug supply chain management

Background

Supply of anti-TB drugs is managed by the CTD, which procures, allocates and distributes medications to all states in the country based on the respective caseloads. Access to accurate forecasts about drug utilization, including inventory, expiry, storage capacity, and logistics, at the most granular level can help the CTD ensure seamless supply and minimise wastage.

Problem & Challenges

Instances of shortages or expiry of anti-TB drugs happen due to an inefficient supply chain, a result of lapses that can occur at any level. Such incidences affect smooth delivery patient care, from causing delays in treatment initiation, interruption in treatment, loss of patients in the care cascade and more broadly, lead to a loss of faith in the overall system.

Opportunity

An AI algorithm can rapidly analyze data on drug inventory quickly and provide timely guidance to meet demand. It can both monitor and predict new facility consumption patterns and forecast seasonal demand. Anticipating future trends that factor in the capacity of drug stores to mobilize specific drugs can minimize the costs of overstocking and expiry of drugs.

Potential inputs for this solution can be data on drugs and logistics, usage, stock availability, and associated impact on patient management. The AI solution will automate decision support by converging demand and supply and guide programme managers to transfer the stock to the store where it requires the most to ensure uninterrupted supply of material.

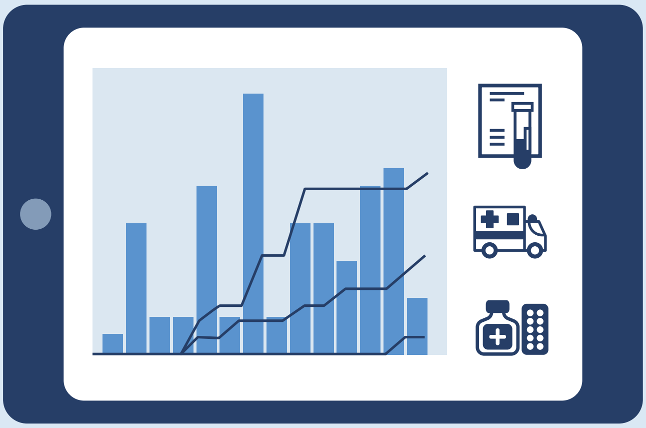


Exhibit 11 : A mock-up of a forecasting system that can help plan logistics for drugs, diagnostics, and medical transport.

Potential users

Drug stock managers.

Healthcare provider networks

Background

Standards for TB Care have been defined by NTEP[29] to ensure consistent quality of care across public health facilities as well as the private sector including clinics, hospitals, doctors and support staff. In 2019, 25% of TB patients were notified from the private sector[30]. Through substantive recent efforts, the NTEP has registered more than 2.5 lakh healthcare providers who can be leveraged to support TB patients with free services and help them link with social benefit schemes.

Problem & Challenges

Despite large-scale engagement efforts, a sizable number of TB cases go unreported29. Health care staff and programme managers face difficulty in prioritizing efforts when engaging with private care providers.

Opportunity

An AI solution can objectively assess and rank the treatment practices and quality of care provided by private health facilities, by analysing patient outcomes, prescriptions and feedback from surveys, to help the NTEP target those in need of improvement. Additional training, reference material and education on best practices can then be offered to help bring these

practices can then be offered to help bring these providers in line with national standards of care.

Potential inputs for this solution can be private health care provider characteristics, facilities available, clinical care practices, patient load, alongside drug sales patterns in relevant geographies.

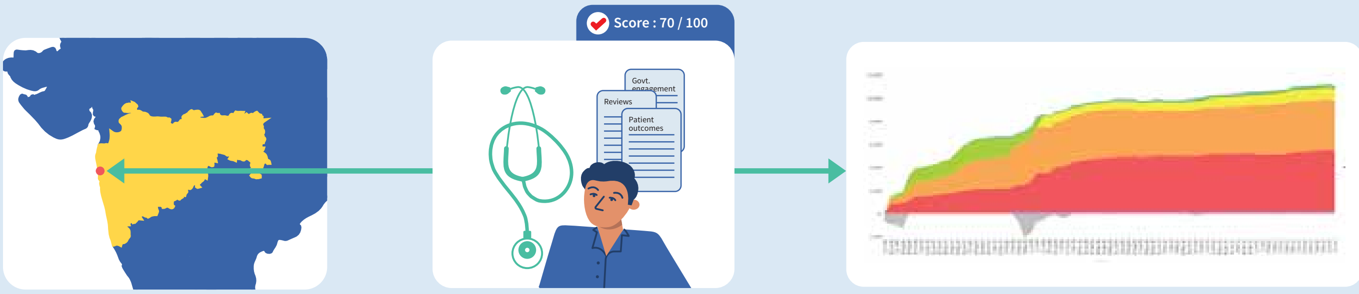


Exhibit 12 : AI can help target private sector care providers based on data such as caseload and patient surveys.

Potential users

Programme managers and engagement staff.

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[29] Standard for TB Care in India
[30] India TB Report 2019

Improve data quality

Background

The NTEP collects vast amounts of data in both paper and digital form. Nikshay alone captures more than 2 million patients' records every year. Currently, the system includes data quality checks to ensure completeness of key information, data consistency, as well as a basic deduplication function.

Problem & Challenges

Though Nikshay was designed to be a paperless system, it is common practice for patient data to be first recorded on paper and digitized later. Patients may move between centres in the middle of treatment for a multitude of reasons. As more and more care providers are onboarded, this increases the potential sources for patient information, and adds to complexity. Inconsistencies and duplicate records become hard to resolve. Staff from different facilities may end up recording the same patient's information, which can jeopardize patient care. The NTEP aims to evolve to a paperless information system.

Opportunity

Digital records can be digitized using existing AI tools such as optical character recognition, speech-to-text and other NLP methods to make data entry faster, more accurate and easily verifiable. More sophisticated functions can facilitate deduplication of records and better linkages to ensure an interrupted continuum of care. Potential inputs for this solution can be the images of paper-based records and digital data records.

Expected outputs can be:
• Pinpointing duplicate records for efficient resolution
• Digitized and machine-readable data

Exhibit 13 : An AI solution that aggregates data from multiple sources and converts them into a single usable database.

Potential users

Frontline health workers who are responsible for data collection and compilation.

Additional use cases

Beyond the scope of use cases described in this document, additional AI-based solutions that could support health systems to tackle specific challenges are listed below:

Diagnostics & decision-making

1. Planning efficient sample collection
2. Genomics-based diagnostic tools
3. Automated HRCT (High-Resolution CT) interpretation
4. Point-of-care ultrasound for extra-pulmonary TB screening
5. Prioritize patients for surgery based on CXR and other reports
6. Optimizing vDOTS tool through movement recognition
7. Networked optimisation of diagnostics
8. Clinical decision support system for care providers and clinicians
9. Manage staff training requirements & resource allocation

Treatment Adherence

10. Remote monitoring tools
11. Weight prediction for nutritional status monitoring
12. Predicting ADRs among patients
13. Voicebots for TB helplines

Prevention & Case detection

14. Identification of vulnerable populations
15. Predict population groups that may develop higher prevalence of DR-TB and NTM or Nontuberculous mycobacteria (Symptom-positive but CBNAAT negative)
16. Analyse social networking platforms to predict high active TB cases
17. Predict contacts that are most likely to develop active TB

Conclusion

Digital technologies can accelerate the fight against TB in multiple ways including patient care, operations management, monitoring and supervision, and capacity building. The NTEP has described multiple potential use cases for AI in this document, with the aim of encouraging innovators to venture towards creating solutions for TB across its four key strategic pillars of Prevent, Detect, Treat and Build. Along with USAID and other partners, NTEP intends to work with implementation partners, innovators, and interested parties on digital health innovations. The programme is also open to adapting existing digital and AI-based solutions.

Interested individuals and organizations are invited to submit their proposals or get in touch with the AI Unit of the NTEP.

सत्यमेव जयते

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