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Optimising Tuberculosis Screening Coverage in a Regional Hospital in Thailand: A Multi-Agent Simulation Approach

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Abstract:

Objective: To assess the impact of tuberculosis (TB) screening coverage on infection risks using a multi-agent simulation (MAS) model, based on a case study of a private hospital in northeastern Thailand.

Material and Methods: A hospital-based multi-agent simulation to evaluate TB transmission across 6 screening coverage levels (0%–100%) during peak and off-peak hours was developed. The model was informed by 200 outpatient observations and hospital data collected between October and December 2024 at a private hospital in northeastern Thailand. A risk matrix was constructed to assess clinical, financial, and reputational outcomes based on scenario-based analysis and stakeholder interviews.

Results: The simulation demonstrated that reduced screening coverage substantially increased the risk of TB transmission, with a more pronounced effect during peak hours. At full coverage, infection rates were 0.61 percent during peak hours and 0.30 percent during off-peak hours. In the absence of screening, these rates increased to 5.50 percent and 0.51 percent, respectively. The higher transmission risk during peak hours reflects the influence of increased patient density and interaction. The risk matrix indicated that limited screening during peak hours led to more severe clinical, reputational, and financial consequences than during off-peak periods.

Conclusion: The findings support the use of MAS as a dynamic tool for evaluating TB screening strategies under real-world constraints. The model highlights how adaptive screening policies, especially during peak hours, can reduce transmission risk and support operational decision-making in resource-limited hospital settings.

Keywords: computer simulation, decision support techniques, infection control, risk assessment, Tuberculosis

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Introduction

Tuberculosis (TB), caused by caused by *Mycobacterium tuberculosis*, continues to be a major public health concern in the Western Pacific Region and worldwide due to its high burden of disease, associated mortality, and the growing challenge of drug resistance[1]. In the aftermath of the coronavirus disease 2019 (COVID-19) pandemic, TB became the second most common cause of death from infectious diseases, reflecting the severe impact of service disruptions on TB detection and treatment[3]. As a chronic infectious disease transmitted through airborne particles, TB predominantly affects populations in crowded and resource-limited environments and remains difficult to eliminate despite the availability of effective treatments[2, 3].

Healthcare facilities are central to both TB prevention and transmission. When screening is delayed or incomplete, hospitals can become environments where TB spreads, particularly through undiagnosed individuals seeking care[4,5]. Although symptom assessments, chest radiography, and sputum analysis are routinely used to identify active TB, these procedures require significant time, human resources, and technical capacity, and may fail to detect early or latent infections[6-8]. Moreover, the risk of exposure among healthcare personnel remains high due to frequent and prolonged contact with suspected or confirmed TB cases[9-13].

To address these operational and clinical complexities, this study applied a multi-agent simulation (MAS) model, which enabled the dynamic evaluation of individual movements, patient interactions, and hospital system responses in relation to TB screening and transmission. In contrast to conventional epidemiological approaches, multi-agent simulation captures spatial and temporal patterns in healthcare service delivery and supports the testing of alternative intervention scenarios under varying conditions[14-17].

This study employed this modelling approach to assess how different levels of tuberculin screening coverage influence the risk of TB transmission within a hospital setting. By integrating patient flow, system capacity, and screening efficiency, the model offers a quantitative perspective on how delayed or insufficient screening may contribute to increased transmission risk. A structured risk matrix was also developed to support evidence-informed decision-making by illustrating the relationship between screening coverage and infection probability. This research aimed to provide a practical framework to assist hospital administrators and public health authorities in optimising TB screening strategies by aligning infection prevention objectives with resource limitations, ensuring patient safety, and strengthening institutional management practices.

Material and Methods

This study used a MAS model to assess the risk of TB transmission under varying screening coverage levels. It also evaluated operational risks, such as patient outcomes, financial burden, and institutional reputation, using a structured risk matrix. The study followed a scenario-based risk assessment framework comprising 3 stages: risk identification, risk analysis, and risk evaluation.

For the first 2 stages, the MAS model was developed using Artisoc[18] to simulate patient arrivals, screening procedures, and interactions within an outpatient department. The model was calibrated using data collected from a private hospital in northeastern Thailand between October and December 2024. This hospital, certified with ISO 9002 and hospital accreditation, provided empirical inputs based on patient flow, spatial layout, and contact proximity. A total of 200 outpatient observations were analysed, along with data from direct observation, hospital records, and interviews with 5 administrators and 10 clinical staff. The average values from these data were used to parameterize the model.

Baseline probabilities related to TB infection were obtained from reports published by the World Health

Organization and other peer-reviewed studies[19-21]. In the model, each simulated patient had a 0.15% probability of being TB-positive upon entering the system[19]. The probability of transmission was based on spatial distance from an infectious case: it ranged from 0.1 to 0.3 when within 2 meters, and from 0.0 to 0.1 when more than 2 meters away [21]. Additionally, it was assumed that 85% of active TB cases were pulmonary TB, which is more infectious[20]. The model simulated 6 screening coverage scenarios: 0 percent, 10 percent, 30 percent, 50 percent, 70 percent, and full coverage, under both peak conditions with 200 patients and off-peak conditions with 120 patients (maximum capacity). The model produced an estimated rate of TB transmission, which was used in the risk evaluation. All parameters used in the simulation are detailed in Supplementary Information A.

In the risk evaluation stage, the parameters were developed based on relevant literature and further refined through consultation with hospital stakeholders, including hospital administrators and clinical leads responsible for TB control, to ensure they reflected practical priorities and institutional realities. This process helped establish a shared understanding of the risks that aligns with local practices and operational experience. These interviews explored institutional priorities and concerns related to infection control. Three major areas of risk were identified: patient health outcomes, the reputation of the healthcare institution, and potential financial consequences. These dimensions represent the broader impacts of reduced TB screening coverage and support the development of more effective and context-specific infection control strategies.

Results

In this research, the occurrence of TB-positive patients entering the hospital was examined in relation to varying levels of TB screening coverage. The analysis compared the number of TB-positive patients in these 2 scenarios, focusing on how patient density under different screening coverage levels affected the incidence of TB-positive cases.

Figure 1 and Table 1 present the TB screening process as implemented in the outpatient department of the case study hospital. Figure 1 illustrates the step-by-step patient flow, beginning from initial hospital entry through screening, diagnostic testing, clinical consultation, and final disposition. It includes decision points based on TB risk assessment, radiological and laboratory results,

Table 1 Process and time of the case study

Activity	Process	Average Time (Minute)	Standby heath worker/patient	Type of Activity
1	General screening test	2.5	1	Operation
2	Check and register medical record	5.32		Operation
3	Lung x-ray	8.75		Operation
4	Waiting for lung x-ray result	10.78		Waiting
5	Sputum test	10.2		Operation
6	Waiting for sputum result	17.62		Waiting
7	Waiting for doctor	20.46		Waiting
8	Meet doctor	10.23		Operation
9	Additional diagnosis	8.45		Operation
10	Move patients to the ARI clinic	7.03		Movement
	Total	101.34	1	

ARI=acute respiratory infection

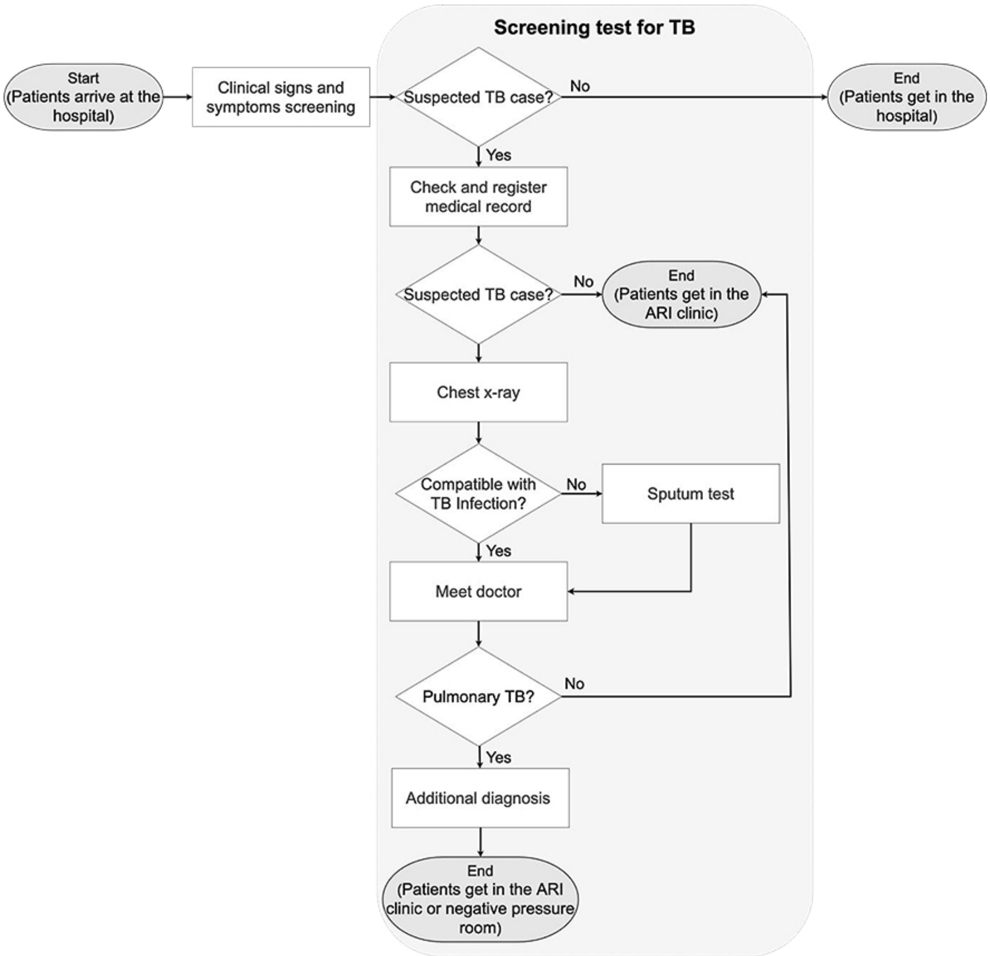

Figure 1 Tuberculosis (TB) screening process flow in the case study hospital

and clinical evaluation. At each step, one health worker is required to be on standby to assist and guide the patient through the process.

Table 1 complements the flowchart by detailing the specific activities involved, along with their corresponding average time durations, the number of staff required per patient, and the functional characteristics of each task. The cumulative average time for the entire TB screening process was 101.34 minutes, reflecting a combination of diagnostic, administrative, and waiting components across all steps.

Figure 2 demonstrates the percentage of TB infections in relation to TB screening coverage during peak hours (with an average of 120 patients) and off-peak hours (with an average of 80 patients). As TB screening coverage decreased, the infection percentage increased more significantly during peak hours. At 100% screening coverage, infection rates were relatively low, with 0.30% during off-peak hours and 0.61% during peak hours. As coverage decreased to 70%, the infection percentage rose to 0.40% during off-peak hours and increased more sharply to 2.86% during peak hours. At 50% coverage, the infection rate grew to 0.49% for off-peak hours and 3.31% for peak hours. Further decreases in screening coverage resulted in slight increases during off-peak hours, reaching

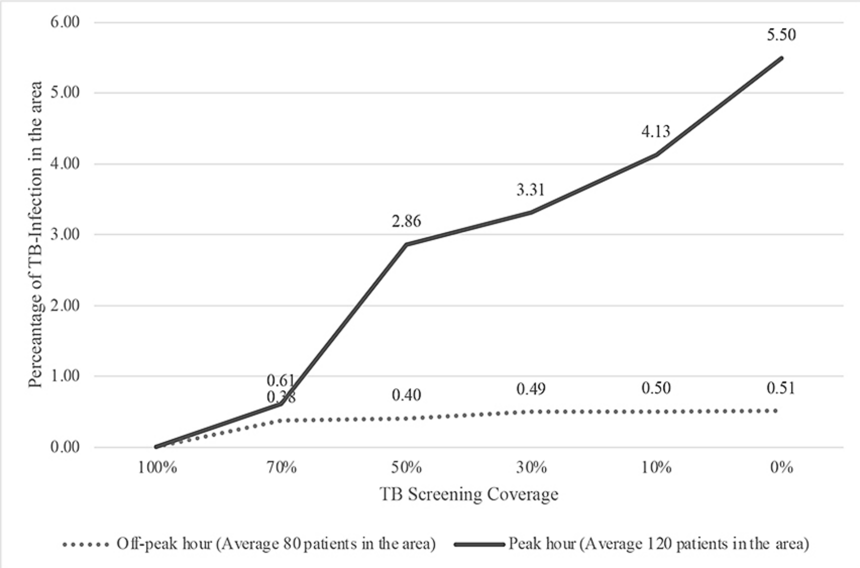

Figure 2 Percentage of tuberculosis (TB) infection

0.51% at 0% coverage, while the infection rate during peak hours rose steeply, reaching 4.13% at 10% coverage and peaking at 5.50% when screening coverage was entirely absent. This figure highlights the importance of maintaining high TB screening coverage, particularly during peak times with high patient density, as the infection percentage increased more dramatically during these periods compared with off-peak hours. The steady rise in infection rates as screening coverage decreased underscores the critical role of comprehensive screening in preventing the spread of TB, especially when healthcare facilities are busy.

During peak hours, TB-positive cases increased as screening coverage declined, with a significant rise observed at 50% and 30% coverage; the highest infection rates occurred at 30% and 0% coverage. This pattern suggests a direct correlation between reduced screening and higher infection rates. Conversely, during off-peak hours, TB cases remained relatively stable across coverage levels, although occasional outliers at 30% and 0% coverage indicated sporadic increases. The findings highlight that screening reduction has a greater impact during peak hours, likely because of higher patient density and increased transmission risk.

Figure 3 illustrates the risk matrix developed for this case study, based on data from interviews with decision-makers. Three key risk domains were identified: patient outcomes, organizational reputation, and financial impact. Risk scoring follows the methodology outlined by the United Lincolnshire Hospitals NHS Trust[22].

From a patient health perspective, the severity of outcomes ranged from the management of mild TB symptoms within the hospital to more severe complications, including death or permanent disability resulting from advanced TB progression. The organisational reputation was similarly affected, with potential consequences escalating from the internal resolution of verbal complaints to formal investigations, increased media scrutiny, and, in extreme cases, widespread public criticism on social media, legal action, and reputational damage. The financial impact followed a corresponding gradient, beginning with

	Insignifaicant (1)	Minor (2)	Moderate (3)	Major (4)	Catastrophic (5)
Patient	Management of minor TB-related symptoms through in-house first aid without medical intervention.	Treatment of TB by medical professionals in outpatient settings, involving mild to moderate cases.	The occurrence of significant but non-permanent health impacts from TB, requiring more substantial medical care.	Permanent health damage from TB, such as lung damage, requiring extended hospital stays and long-term care.	The result of death or permanent disability caused by advanced TB complications.
Health workers (Impact on resource)	Working under a high-risk environment for TB exposure without contracting the infection.(Increased stress and vigilance requirements due to ongoing exposure risk.)	Inability to work due to TB infection, resulting in limited capacity and a minimum two-week disability. (Staffing gaps from worker absence, requiring temporary duty reassignment.)	TB infection causing inability to work, with a minimum two-week disability and additional short-term complications.(Greater demand for medical care, extended recovery time, and increased short-term staffing shortages.)	Long-term disability due to TB infection, requiring at least two months of recovery and ongoing health impacts.(Long-term workforce availability challenges, necessitating prolonged staffing adjustments or hiring.)	Severe TB infection resulting in death or permanent disability of health workers.(Loss of skilled staff, emotional impact on the team, and potential legal or reputational repercussions.)
Reputation	The quick resolution of verbal complaints through internal self-improvement review.	The formal scrutiny of official and written complaints by internal executives or committees.	The local mention of issues through private social media, resulting in short-term media concern.	The long-term brand impact due to the spread of issues across private and public social media.	The significant organizational impact resulting from official public prosecution and brand damage.
Financial	Resolution through negotiation without any official payment required.	A settlement involving 50% payment of the patient's offer.	A financial agreement requiring 70% payment of the patient's offer.	An agreement for 90% payment of the patient's offer, approaching full compensation.	Complete financial settlement with 100% payment of the patient's offer.

Consequence

	TB screening test coverage	TB-infection rate	Likelyhood Score	Insignifaicant (1)	Minor (2)	Moderate (3)	Major (4)	Catastrophic (5)
Likelihood for peak hour	0%	5.50%	3	3	6	9	12	15
	10%	4.13%	3	3	6	9	12	15
	30%	3.31%	3	3	6	9	12	15
	50%	2.86%	3	3	6	9	12	15
	70%	0.61%	2	2	4	6	8	10
	100%	0.00%	1	1	2	3	4	5

	TB screening test coverage	TB-infection rate	Likelyhood Score	Insignifaicant (1)	Minor (2)	Moderate (3)	Major (4)	Catastrophic (5)
Likelihood for off-peak hour	0%	0.51%	2	2	4	6	8	10
	10%	0.50%	2	2	4	6	8	10
	30%	0.49%	2	2	4	6	8	10
	50%	0.40%	2	2	4	6	8	10
	70%	0.38%	2	2	4	6	8	10
	100%	0.00%	1	1	2	3	4	5

Figure 3 Risk matrix of the case study

cases that required no compensation, progressing to partial settlements covering 50% to 90% of the patient's claim, and, in the most severe scenarios, resulting in full financial liability requiring a 100% payout.

The severity of consequences varied significantly between peak and off-peak hours across all 3 dimensions. During peak hours, higher infection rates and lower screening coverage (0%–30%) were associated with a greater likelihood of severe patient outcomes, including an increased risk of complications, disability, or mortality. Inadequate screening coverage further exacerbated reputational risks because hospitals were more likely to receive formal complaints, negative media attention, and potential legal consequences. From a financial standpoint, peak hours posed a higher risk of substantial costs, with settlements often ranging from 70% to 100% of the patient's claim due to the increased severity of cases.

By contrast, off-peak hours were characterised by lower infection rates, which mitigated the severity of patient outcomes and significantly reduced reputational and financial risks. Even at minimal screening coverage levels, the likelihood of severe consequences remained lower than during peak hours. Consequently, during off-peak hours, hospitals had greater flexibility in screening coverage without substantially increasing the risk of critical patient outcomes, reputational harm, or financial liabilities.

Discussion

This study presents a simulation-based framework that applies a multi-agent simulation model to evaluate tuberculosis screening strategies in hospital settings. The model integrates patient flow, interaction patterns, and operational constraints, while linking screening coverage to infection risk, financial cost, and reputational impact. It provides support for evidence-based decision-making, particularly during periods of high patient volume and limited resources.

The findings of this study reinforce existing literature on the importance of early and extensive tuberculosis screening in reducing transmission, particularly in high-density clinical environments. Getahun et al.[23] demonstrated that screening coverage directly affects transmission risk and operational burden during periods of high patient volume. Similarly, Uplekar et al.[10] and Lönnroth et al.[24] emphasized that robust and timely screening protocols are essential for minimizing nosocomial transmission, especially during peak operational hours. This study advances previous work by distinguishing risk levels between peak and off-peak periods. This observation is consistent with infection control literature, which highlights the need for flexible, context-sensitive screening strategies in busy healthcare settings[1,25]. The proposed framework may serve as a planning tool to prioritize screening resources when they are most effective, rather than applying uniform coverage throughout all hours.

The findings are also consistent with recommendations from the World Health Organization, which highlight the need for targeted screening in high-risk settings and during periods of high patient volume[1,9]. In Thailand, particularly in regional hospitals with limited resources, fixed screening protocols may be impractical. This study supports the adoption of adaptive screening policies that prioritize higher coverage during peak hours to reduce tuberculosis exposure and institutional risk, in line with Thailand's National TB Strategy[26]. From a management perspective, incorporating financial and reputational risks into the assessment framework offers strategic value. In resource-constrained environments, quantifying such non-clinical risks may strengthen the case for investing in screening systems, especially in private or accreditation-focused hospitals where institutional reputation is a key concern.

In applying the model, this study moves beyond traditional risk assessments that depend on static assumptions or qualitative scoring methods[10,27]. The multi-agent simulation approach enables real-time scenario testing that reflects the dynamic nature of hospital operations. For example, when screening coverage decreased from full capacity to 40 percent during peak hours, the rate of tuberculosis exposure events rose by approximately 70 percent, underscoring the need for sustained screening during periods of congestion. These results align with prior MAS-based studies[15,17,28], which have shown the utility of agent-based modelling for complex transmission dynamics. This study advances previous work by incorporating operational factors such as time-specific screening capacity and administrative risks into an integrated evaluation framework. In practice, hospitals can apply these findings by prioritizing TB screening during peak hours and adjusting resource allocation accordingly. The model can serve as a planning tool for clinical teams to improve infection control and manage risks during high-traffic periods.

Several limitations should be considered. The model relies on data from a general hospital where both tuberculosis and non-tuberculosis patients are present. As a result, the simulation estimates exposure risk without attributing transmission to specific nosocomial events. The use of fixed transmission probabilities simplifies complex environmental influences such as compliance with mask usage, differences in ventilation quality between hospital areas, and the number of patients during busy periods. For example, high mask compliance among patients and staff can significantly reduce the probability of airborne transmission. Similarly, well-ventilated areas may lower the concentration of infectious aerosols, thereby decreasing exposure risk. A higher number of patients at any given time raises the chance of close contact and crowding, which may elevate the risk of transmission, especially in shared spaces. These factors were not explicitly modeled due to limited data availability, but they should be considered when interpreting the findings and applying them to clinical settings. Sensitivity analysis on screening accuracy was not conducted due to a lack of case-specific data, which has been noted as an area for future improvement.

Moreover, the observed decline in infection percentages with increased screening coverage, as shown in Figure 2, may partly reflect changes in the denominator rather than actual reductions in transmission, highlighting the need for careful interpretation of proportional data in simulation models. The financial estimates are based on generalized assumptions and would benefit from refinement using hospital-specific or national data. Additionally, the model has not yet been tested in low-endemic areas or with larger populations, which may yield different results. Future applications should validate the framework across diverse epidemiological settings to improve generalizability. Despite these limitations, the model provides useful insights for optimizing screening policies and can be adapted to various clinical settings through its modular structure.

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Conflict of interest

The authors have no conflicts of interest to declare.

Ethics statement

This study was approved by the Naresuan University Institutional Review Board (Project No: P1-0166/2567). All procedures were conducted in accordance with institutional guidelines and ethical standards. As the data collection involved simulation modelling and did not include identifiable personal data, informed consent was not required.

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