ARTICLE

Age-structured modeling of tuberculosis transmission in the Philippines

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ABSTRACT

The Philippines is one of the countries with a high number of tuberculosis (TB) cases in the world according to the World Health Organization (WHO). TB incidence in the Philippines has remained consistently high over the years, with an estimated 561,000 incident TB cases in 2020. Around 18% of these cases were recorded among children aged 0–14 years, 72% among Filipinos aged 15–64 years, and the remaining 10% among older adults aged 65 years and above. In this work, a mathematical model with age groupings in the susceptible class—children, the working-age group, and older adults—was developed to describe TB transmission in the Philippines. Sensitivity analysis was also performed to determine the parameters that would pose a significant effect on the model output. Then, key parameter values of the model were estimated using the collected Philippine TB incidence data from 2005-2020. Moreover, the End TB strategy goal initiated by the WHO was assessed to determine mitigating strategies appropriate for the TB transmission in the Philippines Results show that transmission rates among susceptible children and working-age adults affect TB incidence more than the transmission rate among susceptible older adults. Furthermore, programs targeting individuals with latent TB infection who are more likely to develop active TB in the future should be strongly strengthened and prioritized.

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Email Address: mctorres4@up.edu.ph
Date received: 14 September 2025
Dates revised: 06 December 2025
Date accepted: 10 December 2025
DOI: https://doi.org/10.54645/202518SupTEM-96

INTRODUCTION

Tuberculosis (TB) is a communicable infectious disease caused by the bacterium *Mycobacterium tuberculosis* (MTB) (Chai et al., 2018; Koshak et al., 2022). Transmission occurs primarily through cough or sneeze droplets from infected individuals, with prolonged exposure increasing the risk of new infections (Okram & Singh, 2024). MTB infection can affect multiple organs in the body, including the lungs, brain, bones, kidneys, and liver (Arsyad et al., 2024; Verma et al., 2024). Following exposure, an individual may develop either latent or active TB infection (Boom et al., 2021; Salgame et al., 2015). Latent TB cases are infected but do not exhibit symptoms and are not able to transmit the disease (Oh et al., 2025; Shah & Dorman, 2021). In contrast, those with active TB infection display symptoms and are capable of spreading MTB to others (Achour & Chebbi, 2022; Blumberg & Ernst, 2016; Lin & Flynn, 2010). Untreated active TB may result in severe complications or death (World Health Organization, 2021b).

TB remains a major global health threat. According to the US Centers for Disease Control and Prevention, approximately two billion people worldwide are infected with MTB, with about 10 million developing active TB infection annually (Centers for Disease Control and Prevention, 2011). In the Philippines, TB continues to be a significant concern—an estimated 591,000 cases occurred in 2020, but only 268,000 were officially notified (Department of Health, 2020). This places the Philippines among the countries with persistently high TB incidence (World Health Organization, 2022). TB is the sixth leading cause of morbidity and mortality in the Philippines, with a death rate of 28 per 100,000 as of 2020 (World Data Bank, 2020; World

KEYWORDS

tuberculosis, epidemic model, age groupings, TB transmission

Health Organization, 2021a). The COVID-19 pandemic has further strained health services, reducing treatment coverage and notification rates (Department of Health, 2021). Despite ongoing efforts by the Department of Health's National Tuberculosis Control Program, there remains an unmet need for innovative and targeted interventions against TB.

Mathematical modeling is recognized as a valuable approach for studying the epidemiology of infectious diseases and informing public health policies. Previous Philippine TB models have investigated transmission dynamics and intervention strategies. For example, Villasin et al. (2017) demonstrated that improving vaccine coverage alone is insufficient; instead, enhancing partial immunity, treatment success, treatment duration, and case detection is critical for reducing TB incidence and prevalence (Villasin et al., 2017). Kim et al. (2018) applied optimal control theory to determine cost-effective interventions that minimize high-risk latent and infectious cases (Kim et al., 2018). However, past studies generally treated the population as homogeneous and did not explore differences in TB transmission across age groups.

Age-structured mathematical models are essential for understanding transmission dynamics and the mechanisms behind pronounced disparities in TB burden between age groups (Fu et al., 2020). These models enable more realistic projections and inform targeted interventions (Castillo-Chavez & Feng, 1998). Countries such as Taiwan and China have developed continuous age-structured TB models, improving knowledge of the factors contributing to age-related inequalities in TB burden (Brooks-Pollock et al., 2010; Fu et al., 2020; Zhao et al., 2017). It was observed from previous works that young people in the Philippines may be exposed to multiple extended respiratory contacts per day, which may put them at risk of acquiring infection that can develop into TB disease (Snow et al., 2018). Moreover, old adolescents (15-19 years old) spend a huge portion of their time in either public places like schools and malls or mingling with their peers (Lerner & Steinberg, 2009). In addition, about 45.63 million Filipinos aged 15–64 years are currently employed, with an estimated average working time of 40.1 hours per week (Philippine Statistics Authority, 2020). These observations demonstrate the importance of accounting for mobility and social interaction differences across age compartments.

This study addresses the existing research gap by developing an age-structured mathematical model for TB transmission in the Philippines, calibrated to incidence data from 2005-2020. The model estimates key parameters, assesses sensitivity, and evaluates the feasibility of reaching WHO's 2030 End TB Strategy goal of an 80% reduction in TB incidence (Stop TB Partnership, 2019; Vianzon et al., 2013). The findings offer evidence-based strategies to mitigate TB across different age groups and provide updated recommendations for reducing and eventually eliminating TB in the Philippines.

METHODS

Model

The tuberculosis model in this study was adapted from the work of Kim et al. (2018). The entire Philippine population is divided into four epidemiological compartments: susceptible (S), high-risk latent (E), infectious (I), and low-risk latent (L). The susceptible class consists of uninfected individuals who can become infected with TB. The high-risk latent class includes those infected with MTB who have a high probability of progressing to active TB but are not yet infectious to others. The infectious class contains individuals who are symptomatic and capable of transmitting the infection. The low-risk latent class includes people infected with MTB who have a low chance of progressing to active TB and are non-infectious; this class also incorporates individuals who have recovered from the disease but in whom the bacteria persist asymptomatically (Kim et al., 2018).

To analyze age-specific transmission dynamics, the susceptible class is further stratified into three age groups—children (0–14 years, S_1), working group (15–64 years, S_2) (Philippine Statistics Authority, n.d.), and older adults (65 years and above, S_3). The model assumptions include a birth rate (b) contributing to the susceptible population and a uniform natural death rate (μ) applied across all compartments. Transmission rates ($\beta_1, \beta_2, \beta_3$) vary by age group to reflect differential contact patterns among children, working-age adults, and older adults. Movement from children to working group and from working group to old adults occurs at rates (m_1) and (m_2), respectively. Active TB leads to TB-induced mortality at rate (d_T) within the infectious class. Treatment is administered at rate (r) with a failure rate (p). Individuals move from the high-risk latent to the low-risk latent class at rate (α), and from the high-risk latent to the infectious class at rate (κ).

The model assumes no migration, which is reasonable over the medium term in the Philippine context. Homogeneity is assumed within compartments and age groups, thus considering identical risk and behavior in members of the same group. Given the reported differences in social behavior of individuals belonging to various age groups in the Philippines (Philippine Statistics Authority, 2020; Snow et al., 2018), stratifying transmission by age is biologically plausible. Further dividing the latent compartment to high- and low-risk classes aligns with clinical evidence on progression and infectiousness differences (Oh et al., 2025; Shah & Dorman, 2021). The imperfect nature of TB treatment, which may render infected individuals asymptomatic but not eradicate bacteria, is also incorporated (Rangaka et al., 2015).

Despite its strengths, the model has limitations. It does not account for heterogeneity arising from strain variations (Sinha & Rahul, 2023), HIV co-infection (Gao et al., 2024), socioeconomic factors (Cioboata et al., 2025), or migration patterns (Tavares et al., 2017) that can impact TB dynamics. The natural death rate is held constant across compartments and age groups, which could oversimplify demographic variability. Treatment failure may depend on adherence and drug resistance but is modeled with a constant rate (Alinaitwe et al., 2025). Aging transitions between groups are also assumed to be fixed. Parameter values were estimated using Philippine TB incidence and demographic data from 2005 to 2020, ensuring relevance to the local context. Literature-sourced or assumed parameters introduce uncertainty, but sensitivity analyses identify which parameters most influence model outcomes, guiding confidence in projections.

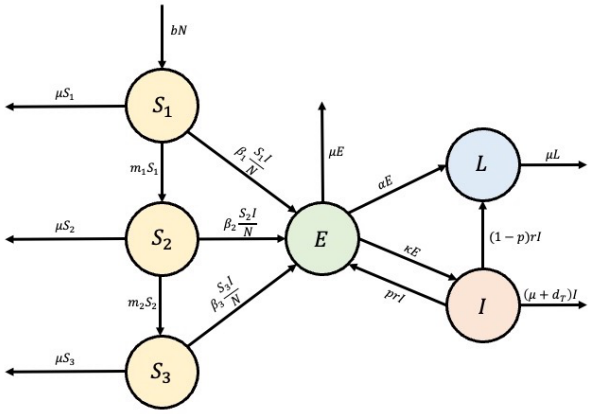


Figure 1: Flow diagram of TB dynamics with age groups. Six classes were considered namely: the susceptible children (S_1); the susceptible

working class (S_2); the susceptible old adults (S_3); the high-risk latent TB class (E); the TB-infected individuals with symptoms (I); and the low-risk latent class (L). The arrows show the flow of individuals from one compartment to another.

The compartmental diagram shown in Figure 1 provides a visual representation of the age-structured tuberculosis (TB) transmission model discussed earlier. The TB transmission in the Philippines is then governed by the system of differential equations as shown in Equation 1.

$$\begin{cases} \frac{dS_1}{dt} = bN - \left(\frac{\beta_1 I}{N} + m_1 + \mu\right) S_1 \\ \frac{dS_2}{dt} = m_1 S_1 - \left(\frac{\beta_2 I}{N} + m_2 + \mu\right) S_2 \\ \frac{dS_3}{dt} = m_2 S_2 - \left(\frac{\beta_3 I}{N} + \mu\right) S_3 \\ \frac{dE}{dt} = \frac{I}{N}(\beta_1 S_1 + \beta_2 S_2 + \beta_3 S_3) + prI - (\alpha + \kappa + \mu)E \\ \frac{dI}{dt} = \kappa E - (\mu + d_T + r)I \\ \frac{dL}{dt} = \alpha E + (1-p)rI - \mu L \end{cases} \quad (1)$$

where N denotes the total population of the Philippines. This pertains to all the persons present in the system at time t i.e. $N = S_1 + S_2 + S_3 + E + I + L$.

Data Collection

The World Health Organization has a dedicated Global Tuberculosis Report website, where updates about the annual TB situation worldwide are reported in this website (World Health Organization, 2022). On the other hand, the World Data Bank also stores information regarding global health and population statistics, including the Philippines (World Data Bank, 2020). The data on the life expectancy at birth, the Philippine TB incidence, the TB-induced mortality rate (per 100,000 people), and the treatment success rate per year from 2005 to 2020 were obtained from these databases.

In addition to the data mentioned above, data on the Philippine population are also necessary for parameter estimation and data fitting. The Philippine population for each age group, as well as the total population from 2005 to 2020, are obtained from the World Data Bank (World Data Bank, 2020).

Estimation of Natural Death Rate (μ) and Birth Rate (b)

In the computation of the natural death rate (μ), the median age of the population and the life expectancy at birth were used. The average life expectancy from 2005 to 2020 was computed, and the median age of the population was subtracted from this average. The natural death rate was estimated to be the inverse of the obtained difference which has a value of $\mu = 0.0225$. The annual birth rate was estimated by minimizing the sum of squared errors between the observed total population and the model solution $\frac{dN}{dt} = (b - \mu)N$ using the MATLAB function *lsqcurvefit*. The total Philippine population from $2005 - 2020$ was used as an input data for the *lsqcurvefit* solver. The annual birth rate was estimated to be $b = 0.0389$. Figure 2 shows the actual and the estimated Philippine population from 2005 to 2020.

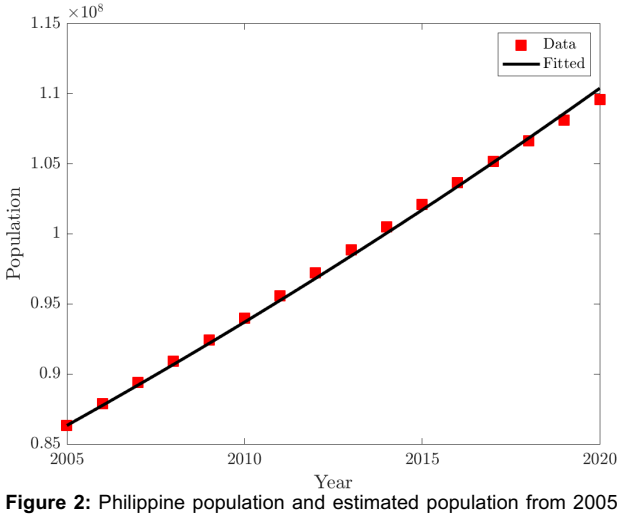


Figure 2: Philippine population and estimated population from 2005 to 2020. The red squares and the black line represent the actual population data and the fitted curve, respectively. An increasing linear trend can be observed in the population from 2005 to 2020.

Estimation of TB-induced Mortality Rate (d_T) and Probability of Failed Treatment (p)

The value of d_T was estimated by getting the average number of Philippine TB-mortality per year from 2005 to 2020. From the data, the TB-induced mortality rate (d_T) was estimated to be 0.0532. While the probability of failed treatment (p) was calculated by getting the difference between 1 and the average treatment success rate from 2005 to 2020. The obtained value for p is 0.1180.

Estimation of Conversion Rates (m_1 and m_2)

The conversion rates refer to the rates at which people move from one susceptible age group to another. These values were estimated using the system of differential equations in equation 2 which reflects the change in population in each group without considering the number of infected people.

$$\begin{cases} \frac{dS_1}{dt} = bN - (m_1 + \mu)S_1 \\ \frac{dS_2}{dt} = m_1 S_1 - (m_2 + \mu)S_2 \\ \frac{dS_3}{dt} = m_2 S_2 - \mu S_3 \end{cases} \quad (2)$$

Together with the data on Philippine population from 2005 to 2020 of the three groups, i.e., $0 - 14$ years old, $15 - 64$ years old, and 65 years old and above, the values of the parameters m_1 and m_2 were estimated using the nonlinear Least-Square method, or the *lsqcurvefit* from MATLAB. Figure 3 shows the data fitting for the said parameters. The estimated parameter values were $m_1 = 0.0906$ and $m_2 = 0.0046$.

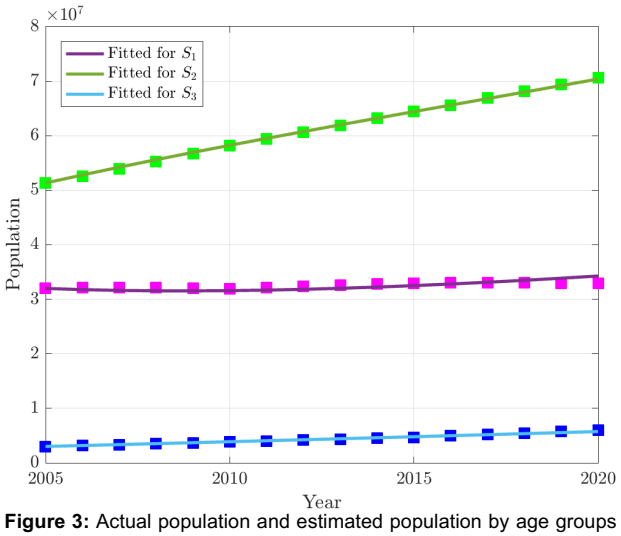


Figure 3: Actual population and estimated population by age groups from 2005 to 2020. The purple, green, and blue squares represent the actual Philippine population of groups $\mathbf{0-14}$ years old, $\mathbf{15-64}$ years old, and $\mathbf{65}$ years old and above, respectively. Similarly, the purple, green, and blue curves represent the fitted curve for groups $\mathbf{0-14}$ years old, $\mathbf{15-64}$ years old, and $\mathbf{65}$ years old and above, respectively.

Sensitivity Analysis

Sensitivity analysis is the study of how levels of uncertainty in the model input might be attributed to different sources of uncertainty in the model output (Saltelli, 2002). Also, it is frequently used to quantify the effect of each parameter on the model outcomes (Hoops et al., 2016). One method for sensitivity analysis is Latin Hypercube Sampling combined with Partial Rank Correlation Coefficient (LHS/PRCC), which was used in this study. It is a method used to examine the complete parameter space of a model in the shortest possible amount of computer simulations (Blower et al., 1991).

The PRCC values of each parameter were obtained using the Latin Hypercube Sampling (LHS). In LHS, each model parameter was assigned a uniform distribution and sampling was done independently. A total of 10,000 simulations were conducted, each with a different set of parameter values chosen from a uniform distribution. To investigate how changes in the parameter affect the model output, time points of interest are identified. As a result, the PRCCs of the model output at specific instances are calculated for each parameter. The model output shows the effect of each parameter to the infectious class, I, with 16 time points representing the range of year considered in the study. The PRCC values of each parameter are presented in Figure 4.

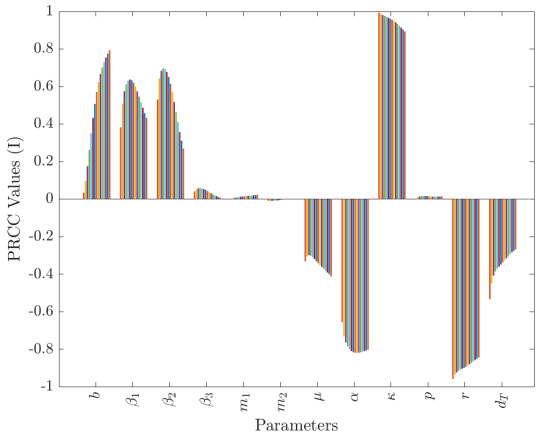


Figure 4: PRCC values that depict the sensitivities of the model output $\boldsymbol{I}$ with respect to the parameters. Parameters $\boldsymbol{b, \beta_1, \beta_2, \mu, \alpha, \kappa, r}$, and $\boldsymbol{d_T}$ have significant effect on the model output.

PRCC values range from -1 to $+1$, and parameters with PRCC values less than -0.5 or higher than 0.5 indicate stronger relationship with the model output (Taylor, 1990). Parameters such as the birth rate (b), transmission rates of children and working groups (β_1, β_2), and the high-risk-latent-to-infectious conversion rate (κ) exhibit high positive PRCC values. A one-unit increase in any of these parameters leads to a corresponding rise in the total number of infectious individuals in the population. In contrast, parameters like the natural mortality rate (μ), progression rate from high-risk latent to low-risk latent class (α), treatment rate (r), and TB-induced mortality (d_T) have high negative PRCC values, indicating that increases in these parameters cause a decrease in the number of infectious individuals.

Parameter Identification

Parameter estimation enables the model to quantitatively reflect the disease dynamics observed in a specific setting. In this study, the model parameters were identified by calibrating the model with the national TB incidence data reported by the Department of Health from 2005 to 2020. No additional adjustment was made to the dataset.

Fitting was performed by minimizing the sum of squared errors between the observed annual TB incidence and the model-predicted incidence, as implemented using the MATLAB routine *fminsearch*. The model output matched to the observed data was the annual number of individuals progressing from high-risk latent TB (E) to infectious TB (I), calculated as the product of the progression rate κ and the high-risk latent population size at each time point.

The parameters calibrated through fitting included the transmission rates for children (β_1) and working group (β_2), progression rate to active TB (κ), and treatment rate (r). Bounds for each parameter were set based on biologically plausible ranges informed by both literature and national demographic statistics. Initial guesses for the parameters were based on a previous modeling study (Kim et al., 2018). Parameters not fitted from data (e.g., transition rates m_1, m_2 and natural death rate μ) were estimated from population statistics or obtained from published prior TB modeling study (Kim et al., 2018).

For initial conditions, the susceptible population sizes for each age group (S_1, S_2, S_3) were set to their respective demographics as reported in the 2005 census data. From the study conducted by Lara and Ocampo, it was determined that about 67% of the Philippine population have latent TB infection (Lara & Ocampo, 2013). The percentage of population with high-risk latent TB and low-risk latent TB were set to 9.5% and 57.5%, respectively. The initial value of the Infectious (I) class was assigned based on the first available incidence data point.

The estimates for β_1 and β_2 are slightly higher compared to the values estimated in previous TB modeling studies in the country for all age groups (Kim et al., 2018; Villasin et al., 2017) reflecting the higher transmission rates in the children and working class. Progression rate from high-risk latent to infectious class (κ) is higher compared to the estimated value reported in (Kim et al., 2018). This is attributed to the higher estimates of the incidence of TB used in the current study. The treatment rate is close to the reported value of 63% in 2018 for the Philippines (AIDS Data Hub, 2019). Figure 5 illustrates the fit of the calibrated model incidence output (black curve) to the reported TB incidence data (red squares), while Table 1 summarizes the estimated and referenced parameters used in simulations.

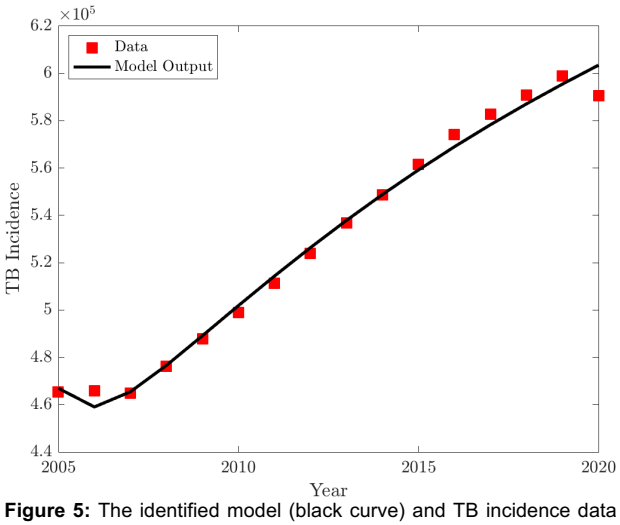


Figure 5: The identified model (black curve) and TB incidence data (red square). Generally, an increasing trend is evident in the Philippines TB incidence.

Table 1: The estimated and data fitted parameter values used in simulations

Parameters	Description	Value	Reference
b	Annual birth rate	0.0389	Data fitted*
μ	Natural death rate	0.0225	Estimated
β_1	Transmission rate of children group	12.9201	Data fitted**
β_2	Transmission rate of working group	12.8587	Data fitted**
m_1	Conversion rate from children to working group	0.0906	Data fitted*
m_2	Conversion rate from working to older adults	0.0046	Data fitted*
κ	Progression rate from high-risk latent to infectious class	0.0569	Data fitted**
r	Treatment rate	0.6590	Data fitted**
d_T	TB-induced mortality rate	0.0532	Estimated
p	Probability of failed treatment	0.1180	Estimated
β_3	Transmission rate of older adults	11.7345	(Kim et al., 2018)
α	Progression rate from high-risk latent to low-risk latent class	0.2077	(Kim et al., 2018)

*Estimated from data on Philippine Population
**Estimated from data on TB Incidence

WHO's END TB Strategy Goal

There have been various efforts exerted by different health institutions to combat the problem of TB burden in the Philippines. Despite these efforts, the incidence rate of TB in the Philippines remains high (World Data Bank, 2020). The Sixty-Seventh World Health Assembly endorsed the End TB Strategy developed by WHO (World Health Organization, n.d.). The organization set a target of an 80% decrease in TB incidence globally by 2030 compared with the number of new TB cases recorded in 2015, which then aims toward ending the TB epidemic. The TB incidence in the Philippines in 2015 was 561,623, so the End TB Strategy goal is to reduce TB incidence to at most 112,325 by 2030. So, to assess the feasibility of reaching the End TB strategy goal of the WHO and determine the best strategy to achieve this target, the researchers considered three mitigating strategies currently implemented by the health institutions of the Philippines. These are also the strategies mentioned in one of the TB paper focused in the Philippines (Kim et al., 2018).

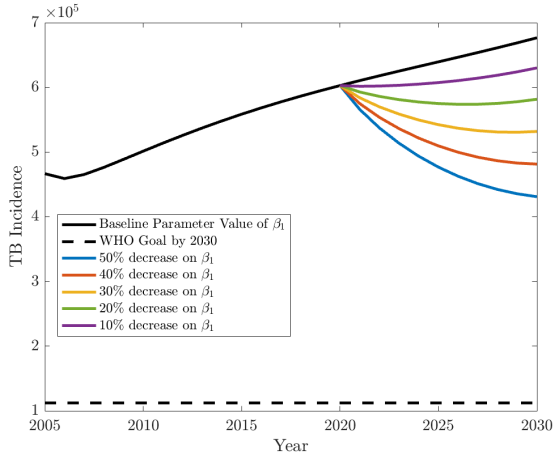
The first strategy is the distancing strategy, which represents all efforts to reduce close contact between susceptible individuals and those with TB. In the model, this is implemented by decreasing the value of the transmission rate (β_1), (β_2), and (β_3). Note that in this paper, we can explore the effects of applying the distancing strategy to different age groups. Another strategy is the latent case finding intervention, which encompasses efforts to prevent high-risk latent TB infections from progressing to active disease. This includes chemoprophylaxis treatment, screening of individuals who have high risk of getting the disease, and other kinds of latent TB treatment. In the model, this strategy was demonstrated by increasing (α). Lastly, the active case finding strategy refers to efforts that increase the number of individuals who seek and receive TB treatment. This was implemented by increasing (r) in the simulations. In the study, several scenarios were considered in attempting to reach the WHO's End Strategy goal. It was assumed that the improvement in the said strategies would be implemented in 2023, and at a constant rate until 2030. First, we varied a single parameter to explore the effect of each strategy. Then, two strategies were implemented by simultaneously varying two parameter values. We also explored the effects of implementing at least three strategies.

RESULTS

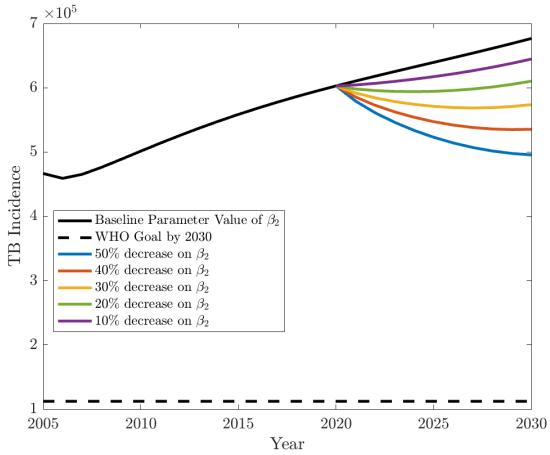
Using the obtained parameter and initial values, the model was simulated over the time span 2005 to 2030. Based on the simulation, TB incidence is projected to reach approximately 676,582, which is about 200,000 higher than the incidence in 2005. This increase implies that there is a need for a more extensive planning and effort to address the TB burden problem in the Philippines. In the next parts of this paper, different strategies to mitigate the disease will be assessed by varying different parameter values.

Variation of a Single Parameter Value

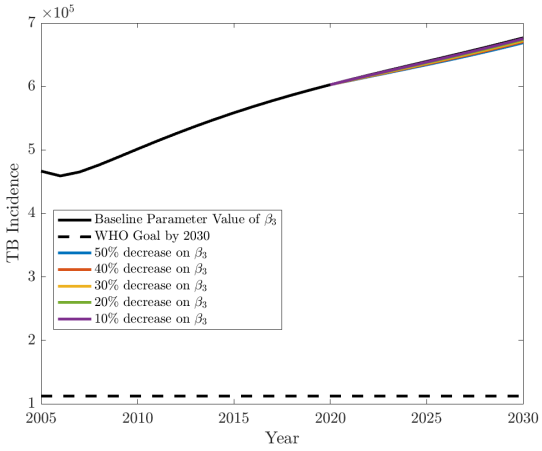
Varying each of the parameters (β_1), (β_2), (β_3), (α), and (r) by $10\% - 30\%$ will not result in the achievement of the End TB strategy goal. Nonetheless, reducing (β_1) and (β_2) by 30% would cause around 19% and 13% decrease respectively in the number of TB incidence while increasing (r) by 30% would result to a decrease of 20% compared to the 2030 projection when no improvement in the current efforts is done. However, when compared to the 2015 incidence data, an estimated decrease of only 2% and 4% is observed when 30% decrease in (β_1) is set and 30% increase in r is implemented. Decreasing (β_3) by $10\% - 30\%$, as shown in Figure 6c, resulted to almost no change in the TB incidence. It is important to note that varying the value of (α) has the capability to strongly decrease the number of TB incidence in the Philippines at around 26% compared to the 2030 projection and 10% compared to 2015 data. As reduction in all scenarios is not sufficient, multiple control strategies were also explored.



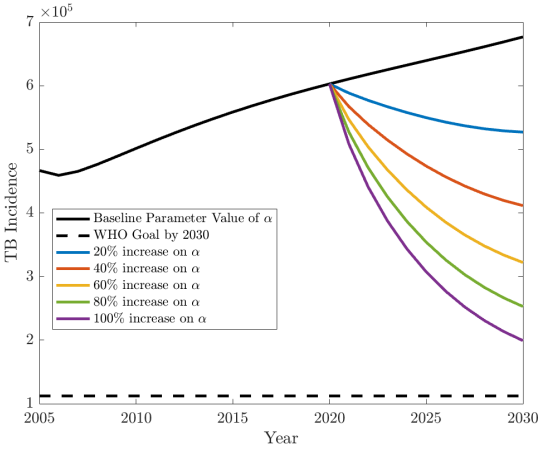
(a) Varying β_1



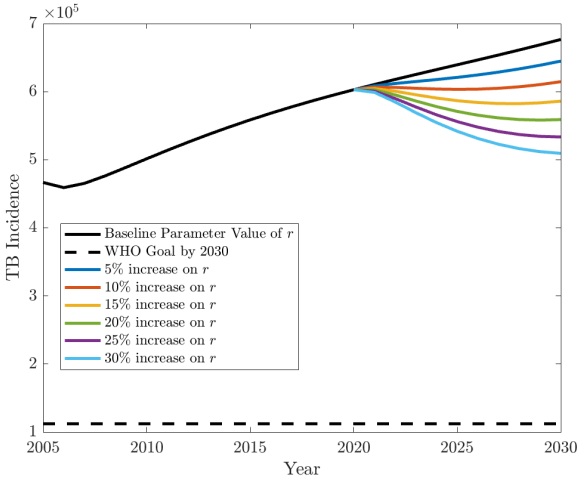
(b) Varying β_2



(c) Varying β_3



(d) Varying α

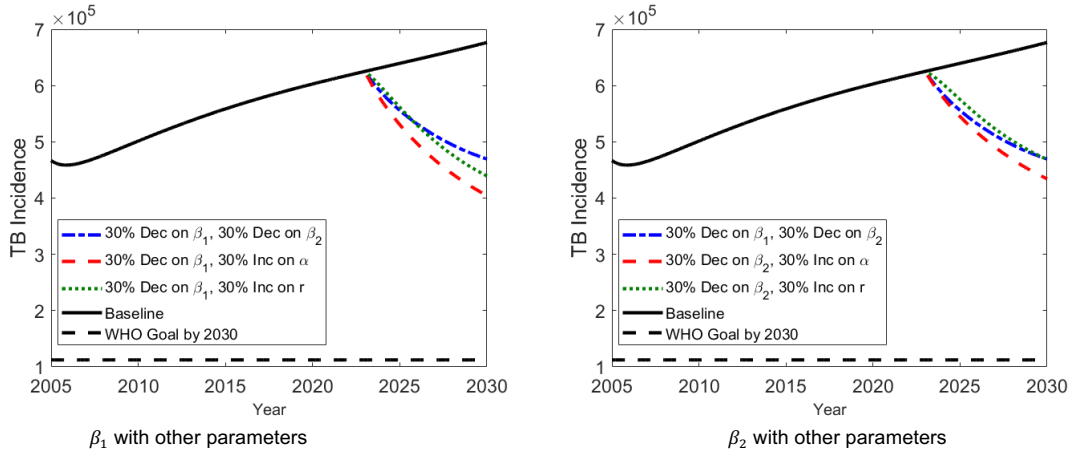


(e) Varying r

Figure 6: The estimated TB incidence when single parameter is varied. Decrease in the incidence is evident when $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, $\boldsymbol{\alpha}$, and $\boldsymbol{r}$ are varied (6a, 6b, 6d, 6e). No significant change in the TB incidence when $\boldsymbol{\beta_3}$ is varied up to **30**% (6c).

Simultaneous Variation of at Least Two Parameter Values

The parameter β_3 was no longer considered in subsequent simulations as the previous section showed that changes in the value of this parameter do not significantly affect the incidence of TB in the country. Starting with a combination of two strategies, the distancing strategy for the children group and the working class were each paired with the other strategies (see Figure 7). For both cases, the distancing strategy together with the latent case finding strategy achieved the lowest incidence by 2030 and resulted in a 28% and 23% lower incidences, respectively, compared to the 2015 incidence.



β_1 with other parameters | β_2 with other parameters

Figure 7: The estimated TB incidence when two parameters are simultaneously changed. Distancing strategy together with latent case finding strategy achieved the lowest incidence by 2030 for both cases

Now, three parameter values were combined to examine their overall effect on the TB incidence in the Philippines. Here, β_1 and β_2 are lowered by 30% while α and r are increased by 30% (see Figure 8). The TB incidence in 2030 will be significantly reduced for each combination. However, the combinations for which α is present displayed the lowest incidences by 2030.

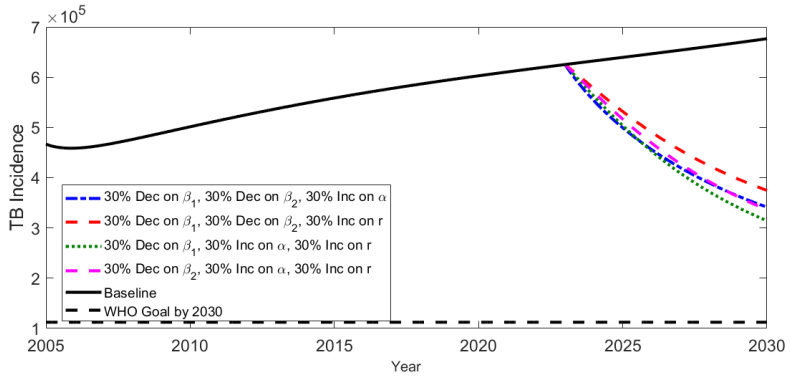


Figure 8: Simultaneously changing three parameter values. Combinations for which $\boldsymbol{\alpha}$ is present displayed the lowest incidences by 2030.

Simulations involving four parameter values were also explored (see Figure 9). Even with 30% decrease in β_1 and β_2 together with a 30% increase in α and r, the projected incidence by 2030 is still far from the WHO goal. In fact, at least 50% decrease in β_1 and β_2, together with 50% and 30% increase on α and r respectively, must be fulfilled to achieve the goal by 2030. Nonetheless, improving each strategy by 30% will lower the incidence by almost 53% compared to the incidence in 2015.

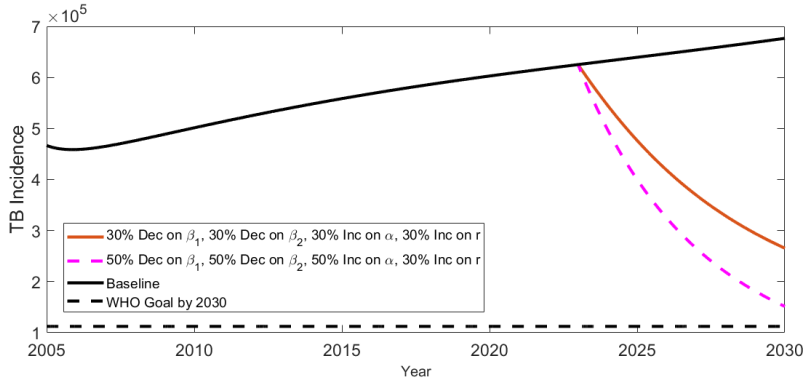


Figure 9: The estimated TB incidence when all parameters are changed simultaneously. At least $\mathbf{50}$% decrease in $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$, together with $\mathbf{50}$% and $\mathbf{30}$% increase on $\boldsymbol{\alpha}$ and $\boldsymbol{r}$ respectively, must be fulfilled to achieve the goal by 2030.

DISCUSSION

Variation of a Single Parameter Value

Varying $(\beta_1), (\beta_2), (\alpha)$, and (r) each by $10\% - 30\%$ resulted in significant but insufficient reductions in infections, implying that minimal efforts to reduce transmission in people aged $0 - 14$ or $15 - 64$ years old or treating more individuals infected with TB alone will not be enough to reduce the number of TB incidence by 80% in 2030. However, these control strategies are significant in curtailing TB in the Philippines.

Decreasing β_3 by $10\% - 30\%$ resulted in almost no change in the incidence of TB. This complements the result of the sensitivity analysis, which showed that β_3 has no significant effect on the model output. Consequently, reducing TB transmission in people aged 65 years and older will not have a large impact on lowering overall TB incidence in the model. However, it is still necessary to pay attention to lowering transmission in this age group. This is because once people in this group become infected with MTB, treatment can be complicated due to current health complications, immune senescence, and other health factors in this age group. In addition, older people tend to show unusual symptoms of TB, leading to delayed diagnosis and treatment resulting in higher morbidity and mortality (Thomas & Rajagopalan, 2001).

Simultaneous Variation of at Least Two Parameter Values

The impact of the latent case finding strategy that was explored by varying α was dominant compared to the active case finding strategy in terms of reducing the TB incidence. The significance of this strategy is still evident in the scenario where three control strategies are improved. The efforts to assist high-risk latent TB individuals must then be improved to effectively mitigate TB in the country. The results displayed a large change in $\beta_1, \beta_2, \alpha,$ and r is required to attain the goal by 2030. This implies that intensive improvement of all efforts related to distancing strategy for children and the working group, latent case finding intervention, and active case finding strategy are necessary. This will be challenging in a situation where there are limited resources. However, enhancing all the mentioned strategies by 30% will result in significant reductions in the incidence of tuberculosis in the country.

Comparison with Similar Studies Across the Asia-Pacific Region

While the model developed in this study introduces age-structuring in TB transmission, it is important to acknowledge that the national TB incidence datasets used were highly aggregated and not age-specific. As a result, direct fitting and validation of each age group in the model is limited by data availability. To address this and to substantiate the conclusions drawn from the model, we compared our simulation results with findings from recent mathematical modeling studies in high-burden and neighboring regions.

Notably, our model's identification of the working-age group as one of the primary drivers of transmission aligns with recent findings from the Republic of Korea. Seong et al. (2025) demonstrated that targeting Latent TB Infection (LTBI) treatment specifically in adults aged 35–64 resulted in the most effective reduction of disease burden, reinforcing our finding that interventions focused on the economically active population result in significant benefits. This also strengthens the claim of the importance of latent case finding strategy as suggested in the current study. Similarly, in the context of Indonesia, Fatmawati et al. (2020) utilized a discrete age-structured model to derive optimal control strategies, highlighting that distinct interventions for child and adult populations are necessary to maximize the reduction of latent and active cases. This supports our modelling framework, particularly the stratification of the susceptible class into these age groups.

Comparisons with studies from China reveal both consistencies and context-specific differences. Xue et al. (2022) found that improved vaccination and diagnostic strategies were most effective when targeting young adults (20–24 years) and the elderly (over 65 years). While this partially aligns with our emphasis on young/working-age adults, our results suggest a lower relative contribution from the elderly compared to the working-age group in the Philippines, whereas Xue et al. emphasize the elderly as a critical target in China's aging demographic.

CONCLUSION AND RECOMMENDATIONS

The results of this study underscore the significant impact of age on the dynamics of TB transmission in the Philippines. Certain age ranges, such as children and working groups, are disproportionately prone to TB infection due to factors including frequency of social contact. To reflect these differences, age compartments were integrated into a mathematical model adapted from the established work of Kim et al. (2018), calibrated using Philippine national TB data.

Sensitivity analyses revealed that TB incidence in the Philippines is highly sensitive to transmission rates among children and the working-age group, whereas transmission among older adults contributes relatively less. This age-stratified approach demonstrates that uniform intervention strategies may neglect key population dynamics, and that targeted efforts for children and working group yield greater impact in reducing TB transmission.

Notably, model-based feasibility assessments of the WHO's End TB Strategy target, an 80% incidence reduction by 2030, showed that focusing solely on singular parameter improvements may be insufficient to reach the goal. However, substantial reductions were observed when increasing the progression rate from high-risk latent to low-risk latent class (α), highlighting the necessity of intensified identification and management of latent TB cases most likely to progress to active disease. Integrated strategies that combine latent TB identification and treatment with improved social distancing efforts in child and working group should be prioritized to reduce TB incidence in the country.

A principal limitation of this study lies in the dependence of numerical simulations on reported TB incidence data, which are subject to under-reporting and case notification inaccuracies in the Philippines (Garfin et al., 2013; Parpieva et al., 2021). Recent surveys indicate the true prevalence of TB is approximately three times higher than the number of notified cases, with even larger discrepancies observed in pediatric and adolescent age groups (Seddon et al., 2018). Such underestimation may result in systematic bias in parameter estimation. Consequently, the simulated projections may underestimate the overall TB burden. While sensitivity analyses were used to evaluate the robustness of model outputs to parameter variations, it is important to interpret the results with caution because inaccuracies in TB case notifications may affect the model's ability to produce accurate projections. Enhanced surveillance data and improved uncertainty measurements are required for future modeling works to better inform health policy.

Biological system modeling is a powerful tool for public health research, particularly in incorporating complex epidemiological concepts and enabling assessment of different interventions. However, several limitations exist specific to modeling TB in the Philippines. The current modeling framework does not account for migration, HIV-TB co-infection or socioeconomic

determinants that may impact TB transmission dynamics. Additionally, the assumption of population homogeneity within age groups and states may ignore important individual-level patterns. Acknowledging these limitations is essential for contextualizing the results from the study.

For future studies, we recommend investigating TB transmission in the Philippines using models with age stratification in the high-risk latent and infectious classes, or in combinations of different compartments, to further analyze how age affects TB transmission. Future researchers may also explore using different (or more) age groups in studying the transmission of TB in the Philippines.

ACKNOWLEDGMENTS

This research is not funded.

CONFLICT OF INTEREST

The authors have no conflicts of interest that are directly relevant to the content of this article.

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