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Martha Wangari Kimando
Kerugoya, Kirinyaga County,
Kenya

Dr. Moffat Chamuchi Nyaboe
Kerugoya, Kirinyaga County,
Kenya

Dr. Rachel Atieno Nyang'inja
Kerugoya, Kirinyaga County,
Kenya

Modelling the impact of tourism in the spread of human immunodeficiency virus in Kenya

Martha Wangari Kimando, Moffat Chamuchi Nyaboe and Rachel Atieno Nyang'inja

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Abstract

Tourism-driven mobility introduces additional transmission pathways for HIV/AIDS that can be rigorously analyzed using compartmental models. In this study, we formulate an SIA model that stratifies the population into Susceptible (S), Infected (I), and AIDS (A) compartments. The model is expressed as a system of nonlinear ordinary differential equations (ODEs), where transitions between compartments are governed by infection rates, progression rates to AIDS, and removal terms due to treatment or mortality. To evaluate the potential for disease invasion, the next generation matrix (NGM) method is employed. The system is linearized around the disease-free equilibrium, and the NGM is constructed by separating new infection terms from transition terms. The basic reproduction number R_0 is obtained as the spectral radius of the NGM, providing a rigorous measure of the average number of secondary infections generated by a single infected individual. Numerical simulations are conducted to explore the dynamics under varying parameter regimes. Deterministic simulations are implemented using numerical solvers to generate time-series trajectories of $S(t)$, $I(t)$, and $A(t)$. Sensitivity analysis is performed to identify parameters with the greatest influence on R_0 and epidemic outcomes, such as tourist arrival rates and average duration of stay. Simulation outputs include prevalence curves, bifurcation diagrams, and parameter sweeps to illustrate threshold phenomena and intervention effectiveness. By integrating the SIA model, analytical derivation of R_0 via the NGM, and computational simulations, this study provides a mathematically rigorous framework for understanding how tourism contributes to HIV/AIDS transmission dynamics, and to inform targeted public health strategies in regions with high tourist activity.

Keywords: HIV/AIDS transmission, mathematical modeling, endemic equilibrium, stability analysis

Introduction

Since the first cases of HIV/AIDS were documented in the early 1980s, it has been one of the major public health issues in Kenya. The epidemic has had wide-ranging impacts, not just on the health of people, but also on the nation's social and economic life. The adult HIV prevalence rate in Kenya is estimated at 3.0%, with significant regional differences. Some counties such as Homa Bay, Kisumu and Siaya have prevalence rates of over 15%, which is higher than the national average. These areas are characterised by high mobility, fishing communities, and urban centres where transactional sex is widespread, thus increasing the risk of HIV transmission in these areas (UNAIDS, 2024) ^[25].

Tourism, however, plays a vital role in Kenya's economy. The sector generates around 10% of the country's GDP and is a source of jobs for thousands of people. Millions of foreign visitors come to Kenya every year to visit its coasts, wildlife reserves and cities. Tourism, nevertheless, poses public health concerns. Tourist destinations have been found to share characteristics with HIV prevalence hotspots, creating opportunities for risk-taking sexual encounters between tourists and locals.

HIV/AIDS transmission dynamics in Africa have been widely investigated using mathematical modelling. Models can be used to estimate the basic reproduction number (R_0), to assess the effectiveness of intervention measures, and to forecast the course of an epidemic. In Kenya, Sirengo (2019) ^[26] developed a deterministic compartmental model to analyze prevention

Corresponding Author:

Martha Wangari Kimando
Kerugoya, Kirinyaga County,
Kenya

measures, dividing the population into susceptible, infected, and AIDS compartments. The study demonstrated the existence of both disease-free and endemic equilibria, highlighting the importance of sustained interventions. Odhiambo (2025) ^[15] extended HIV transmission models by incorporating awareness among adolescents and young adults, showing that behavioral interventions significantly reduce transmission rates. Similarly, Omondi (2020) ^[16] applied mathematical modelling to evaluate the impact of intervention strategies such as ART and condom use, concluding that combined interventions are more effective than single strategies. Beyond Kenya, the HIV Modelling Consortium has coordinated modelling efforts across sub-Saharan Africa to inform policy decisions. Musa *et al.* (2025) ^[13] incorporated treatment and removal strategies into HIV models, demonstrating how mathematical approaches can guide public health planning. These studies underscore the importance of mathematical modelling in understanding HIV dynamics and designing effective interventions.

Despite extensive modelling of HIV/AIDS, few studies explicitly integrate tourism as a factor in transmission dynamics. The intersection of tourism and HIV is critical in Kenya, where tourist inflows create temporary but intense social interactions. By incorporating tourists into

compartmental models as a distinct population with different prevalence rates and contact patterns, this research simulates how tourism influences HIV spread.

2. Model Formulation

We develop a susceptible-infected-AIDS (SIA) mathematical model to study the transmission dynamics of HIV/AIDS in the presence of tourist inflows. The population is divided into three compartments: susceptible individuals (S), infected individuals (I), and individuals with AIDS (A). Tourist inflows are incorporated into the model as an external factor influencing disease transmission dynamics through increased interactions within the population.

The model is formulated using a system of ordinary differential equations describing the movement of individuals between compartments. Qualitative analysis of the model is carried out by establishing the positivity and boundedness of solutions to ensure biological feasibility of the system. The disease-free and endemic equilibrium points are determined, and the basic reproduction number R_0 is derived using the Next Generation Matrix method. Furthermore, the local stability of the disease-free equilibrium is analyzed to determine the conditions under which HIV/AIDS persists or dies out in the population.

Table 1: Model Variables

Variable	Description
$S(t)$	Number of susceptible individuals at time t .
$I(t)$	Number of HIV-infected individuals at time t .
$A(t)$	Number of individuals in the AIDS stage at time t .
$N(t)$	Total population at time t .

Table 2: Model Parameters

Parameter	Description
Λ	Recruitment rate of local susceptible individuals (births or immigration).
T_s	Inflow rate of tourists entering the susceptible population.
β	Effective transmission rate of HIV through contact.
T_i	Inflow rate of tourists entering the infected population.
α	Progression rate from HIV infection to AIDS.
μ	Natural death rate (applies to all compartments).
δ	AIDS-induced death rate (additional mortality in the AIDS compartment).

3. Model Assumptions

- The total population is divided into three compartments, namely susceptible individuals (S), infected individuals (I), and individuals with AIDS (A).
- Individuals enter the susceptible population through recruitment at a constant rate Λ .
- Tourist inflows contribute to the susceptible population at rate T_s and to the infected population at rate T_i .
- Susceptible individuals acquire HIV infection through effective contact with infected individuals at transmission rate β .
- Infected individuals progress to the AIDS class at rate α .
- Natural death occurs in all compartments at rate μ .

- Individuals in the AIDS class experience additional disease-induced death at rate δ .
- Recovery from HIV/AIDS is not considered in the model, since there is no complete cure for the disease.
- The population is assumed to mix homogeneously.

4. Model Flow Chart

The interactions between the compartments of the SIA model and the tourist inflows are summarised in the compartmental flow diagram shown in Figure 1. The arrows represent the movement of individuals into, between, and out of the compartments, together with the recruitment, transmission, progression, and mortality terms.

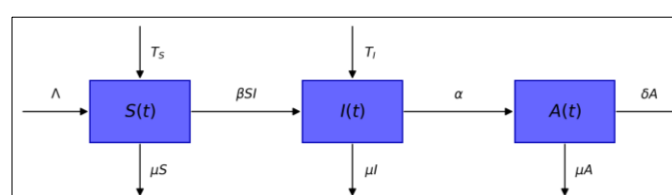


Fig 1: Model Flow Chart

5. Model Equations

Based on the assumptions and the compartmental flow diagram, the dynamics of the susceptible, infected, and AIDS populations are governed by the following system of ordinary differential equations:

$$\frac{dS}{dt} = \Lambda + T_s - \beta SI - \mu S$$

$$\frac{dI}{dt} = \beta SI + T_i - (\alpha + \mu)I$$

$$\frac{dA}{dt} = \alpha I - (\delta + \mu)A$$

6. Model Analysis

The formulated SIA model provides a framework for understanding how tourist inflows influence the dynamics of HIV/AIDS transmission in Kenya. In this section, we analyze the system to determine its equilibrium states, the basic reproduction number, and the stability of the disease-free and endemic equilibria.

6.1 Positivity and Boundedness of Solutions

In this section, it is shown that the solutions of the model remain positive and biologically meaningful for all time $t > 0$. The model equations are considered together with the initial conditions

$$\frac{dS}{dt} = \Lambda + T_s - \beta SI - \mu S$$

$$\frac{dI}{dt} = \beta SI + T_i - (\alpha + \mu)I$$

$$\frac{dA}{dt} = \alpha I - (\delta + \mu)A$$

$$S(0) > 0, \quad I(0) > 0, \quad A(0) > 0$$

6.1.1 Positivity of Solutions

To show positivity, consider the susceptible population equation

$$\frac{dS}{dt} = \Lambda + T_s - \beta SI - \mu S$$

Since $\Lambda + T_s > 0$, it follows that

$$\frac{dS}{dt} \geq -(\beta I + \mu)S$$

Thus,

$$S(t) \geq S(0)e^{-(\beta I + \mu)t} > 0$$

Similarly, for the infected population,

$$\frac{dI}{dt} = \beta SI + T_i - (\alpha + \mu)I$$

Hence,

$$\frac{dI}{dt} \geq -(\alpha + \mu)I$$

Therefore,

$$I(t) \geq I(0)e^{-(\alpha + \mu)t} > 0$$

For the AIDS population,

$$\frac{dA}{dt} = \alpha I - (\delta + \mu)A$$

Since $\alpha I \geq 0$,

$$\frac{dA}{dt} \geq -(\delta + \mu)A$$

Thus,

$$A(t) \geq A(0)e^{-(\delta + \mu)t} > 0$$

Therefore, all state variables remain positive for all $t > 0$.

6.1.2 Boundedness of Solutions

Let the total population be

$$N(t) = S(t) + I(t) + A(t)$$

Differentiating with respect to time gives

$$\frac{dN}{dt} = \frac{dS}{dt} + \frac{dI}{dt} + \frac{dA}{dt}$$

Substituting the model equations,

$$\frac{dN}{dt} = \Lambda + T_s + T_i - \mu S - (\alpha + \mu)I + \alpha I - (\delta + \mu)A$$

Simplifying,

$$\frac{dN}{dt} = \Lambda + T_s + T_i - \mu(S + I + A) - \delta A$$

Since $\delta A \geq 0$,

$$\frac{dN}{dt} \leq \Lambda + T_s + T_i - \mu N$$

Therefore,

$$\frac{dN}{dt} + \mu N \leq \Lambda + T_s + T_i$$

Solving the differential inequality gives

$$N(t) \leq \frac{\Lambda + T_s + T_i}{\mu}$$

Hence, the solutions of the system are bounded in the feasible region

$$\Omega = \left\{ (S, I, A) \in \mathbb{R}^3 : N(t) \leq \frac{\Lambda + T_s + T_i}{\mu} \right\}$$

Therefore, the model is mathematically and biologically well posed.

6.2 Disease-Free Equilibrium (DFE)

At the disease-free equilibrium there are no infections, so that

$$I = 0, \quad A = 0$$

The susceptible population stabilizes at

$$S_0 = \frac{\Lambda + T_s}{\mu}$$

This is the baseline number of susceptible individuals when no infection exists.

6.3 Endemic Equilibrium

The endemic equilibrium occurs when HIV/AIDS persists in the population at a constant level. It is obtained by solving the system of equations with $I > 0$ and $A > 0$. The endemic equilibrium depends on the balance between infection rates, progression to AIDS, and mortality. Its existence requires that the basic reproduction number satisfies

$$R_0 > 1$$

At endemic equilibrium, the model variables remain constant over time. Therefore,

$$\frac{dS}{dt} = \frac{dI}{dt} = \frac{dA}{dt} = 0$$

Let the endemic equilibrium point be denoted by

$$E^* = (S^*, I^*, A^*)$$

Where all compartments are positive.

6.4 Basic Reproduction Number

The basic reproduction number, denoted by R_0 , is defined as the average number of secondary infections produced by one infected individual in a completely susceptible population. The value of R_0 determines whether the disease will persist or die out in the population.

- If $R_0 < 1$, the disease-free equilibrium is stable and the disease dies out.
- If $R_0 > 1$, the endemic equilibrium exists and the disease persists in the population.

The basic reproduction number is obtained using the next generation matrix method.

6.5 Basic Reproduction Number Using the Next Generation Matrix Method

Consider the model equations

$$\frac{dS}{dt} = \Lambda + T_s - \beta SI - \mu S$$

$$\frac{dI}{dt} = \beta SI + T_i - (\alpha + \mu)I$$

$$\frac{dA}{dt} = \alpha I - (\delta + \mu)A$$

The infected compartment is I . The rate of appearance of new infections is

$$F = \beta SI$$

The transfer term is

$$V = (\alpha + \mu)I$$

At the disease-free equilibrium point (DFE),

$$E_0 = \left(\frac{\Lambda + T_s}{\mu}, 0, 0 \right)$$

The Jacobian matrices of F and V evaluated at the disease-free equilibrium are

$$F = \beta S$$

Substituting the disease-free equilibrium value of S gives

$$F = \beta \frac{\Lambda + T_s}{\mu}$$

Similarly,

$$V = \alpha + \mu$$

Therefore,

$$V^{-1} = \frac{1}{\alpha + \mu}$$

The next generation matrix is

$$FV^{-1} = \frac{\beta(\Lambda + T_s)}{\mu(\alpha + \mu)}$$

The basic reproduction number is the spectral radius of the matrix FV^{-1} . Hence,

$$R_0 = \frac{\beta(\Lambda + T_s)}{\mu(\alpha + \mu)}$$

The disease persists in the population when

$$R_0 > 1$$

and dies out when

$$R_0 < 1$$

6.6 Local Stability of the Disease-Free Equilibrium

The local stability of the disease-free equilibrium is determined using the Jacobian matrix of the system. The model equations are

$$\frac{dS}{dt} = \Lambda + T_s - \beta SI - \mu S$$

$$\frac{dI}{dt} = \beta SI + T_i - (\alpha + \mu)I$$

$$\frac{dA}{dt} = \alpha I - (\delta + \mu)A$$

The disease-free equilibrium point is

$$E_0 = \left(\frac{\Lambda + T_s}{\mu}, 0, 0 \right)$$

The Jacobian matrix of the system is

$$J = \begin{bmatrix} -\beta I - \mu & -\beta S & 0 \\ \beta I & \beta S - (\alpha + \mu) & 0 \\ 0 & \alpha & -(\delta + \mu) \end{bmatrix}$$

Evaluating the Jacobian matrix at the disease-free equilibrium gives

$$J(E_0) = \begin{bmatrix} -\mu & -\beta \frac{\Lambda + T_s}{\mu} & 0 \\ 0 & \beta \frac{\Lambda + T_s}{\mu} - (\alpha + \mu) & 0 \\ 0 & \alpha & -(\delta + \mu) \end{bmatrix}$$

The eigenvalues of the matrix are

$$\lambda_1 = -\mu$$

$$\lambda_2 = \beta \frac{\Lambda + T_s}{\mu} - (\alpha + \mu)$$

$$\lambda_3 = -(\delta + \mu)$$

For local stability, all eigenvalues must be negative. Thus,

$$\beta \frac{\Lambda + T_s}{\mu} - (\alpha + \mu) < 0$$

which implies

$$\frac{\beta(\Lambda + T_s)}{\mu(\alpha + \mu)} < 1$$

Hence,

$$R_0 < 1$$

Therefore, the disease-free equilibrium is locally asymptotically stable when

$$R_0 < 1$$

and unstable when

$$R_0 > 1$$

7. Numerical Simulations

The simulations are performed to study the dynamics of the model for various values of the parameters and to examine how infection with HIV/AIDS would be affected by changes in the number of tourists. The system of ordinary differential equations developed above is solved numerically to show the evolution of the susceptible, infected, and AIDS populations over time. The simulations are used to illustrate how disease transmission is affected by important epidemiological parameters such as the transmission rate, progression rate to AIDS, natural death rate, and rates of tourist inflow.

7.1 Parameter Values and Initial Conditions

Numerical simulations of the model were performed with parameter values selected from the literature, together with assumptions based on the dynamics of HIV/AIDS transmission in regions affected by tourism. The initial conditions were selected to reflect the interaction among the susceptible, infected, and AIDS populations in the context of tourist inflows. The initial conditions used for the simulations were

$$S(0) = 1000, \quad I(0) = 50, \quad A(0) = 10$$

Table 3: Model Parameters and Their Values

Parameter	Description	Value
Λ	Recruitment rate into susceptible population	500
β	HIV transmission rate	0.0004
α	Progression rate to AIDS	0.03
μ	Natural death rate	0.01
δ	AIDS-induced death rate	0.02
T_s	Tourist inflow into susceptible class	50
T_i	Tourist inflow into infected class	5

The simulations were carried out using MATLAB to illustrate the behaviour of the model compartments under varying tourist inflow conditions.

7.2 Dynamics of the Susceptible Population

Figure 2 shows the variation of the susceptible population over time. The results indicate that the susceptible population decreases gradually as individuals become infected through contact with infected individuals and tourists.

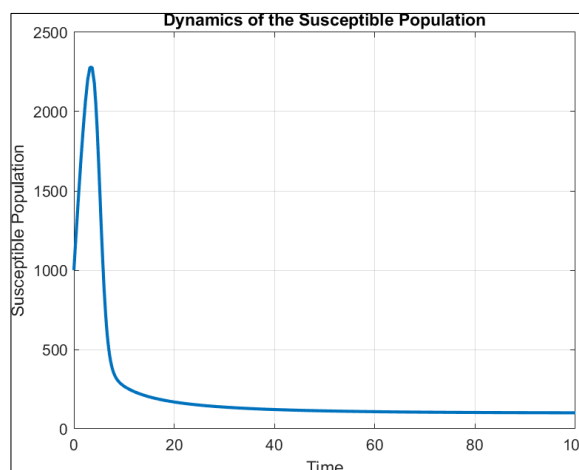


Fig 2: Dynamics of the susceptible population

7.3 Dynamics of the Infected Population

Figure 3 shows the variation of the infected population over time. The results indicate that the number of infected individuals increases due to effective contact between susceptible individuals, infected individuals, and tourists. The trend highlights the contribution of tourist inflows in sustaining the infection within the population.

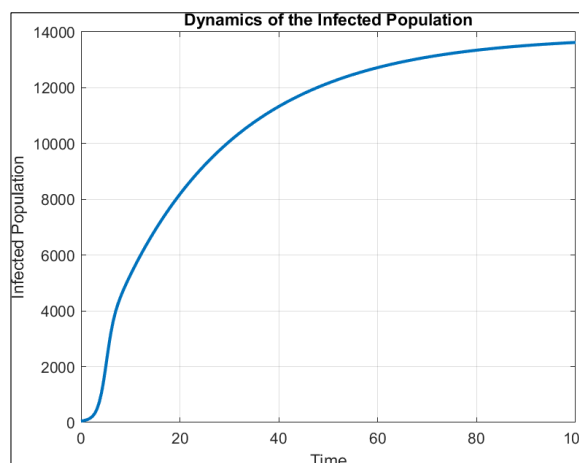


Fig 3: Dynamics of the infected population

7.4 Dynamics of the AIDS Population

Figure 4 illustrates the progression of infected individuals into the AIDS class over time. The results show an increase in the AIDS population due to progression from the infected class at rate α and the effects of disease-induced mortality.

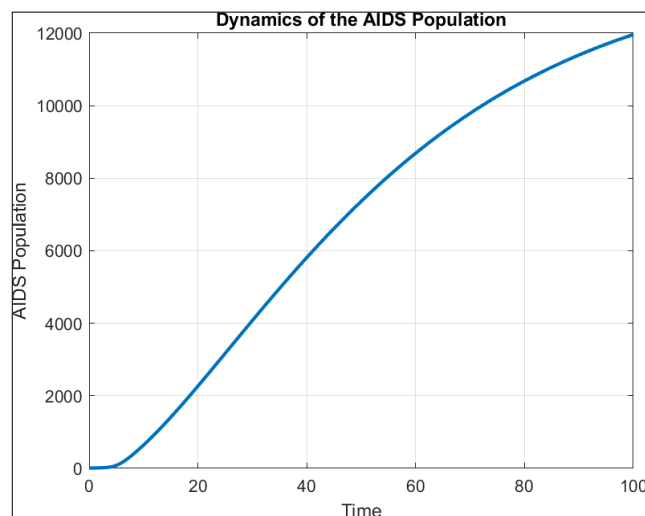


Fig 4: Dynamics of the AIDS population

8. Model Validation

The realism of the proposed model is evaluated by comparing the simulation results with reported HIV/AIDS trends in Kenya available from national health reports and the literature. HIV prevalence in Kenya has gradually decreased over the years as people have become more aware, more programs have become available for treatment, and more interventions have been introduced to prevent HIV. However, in tourist-frequented areas, there have been outbreaks of higher-than-normal infection rates.

8.1 Data Description for Model Validation

The real data used for validation of the model is based on estimates from the Joint United Nations Programme on HIV/AIDS (UNAIDS) and the National Syndemic Disease Control Council (NSDCC) of Kenya. According to UNAIDS (2024), Kenya has approximately 1.3 million people living with HIV, with an adult prevalence of about 3.0% to 3.7%. The country records approximately 17,000 to 20,000 new HIV infections annually and about 20,000 AIDS-related deaths per year. For the purpose of model validation over a period of 36 months (3 years), the annual data is converted into monthly estimates as follows^[25]:

- Average new infections per month $\approx 1,400$.
- Average AIDS-related deaths per month $\approx 1,600$.

These values are used to construct a comparative dataset for validating the infected class $I(t)$ in the model.

8.2 Data Sources

The data used in this study was obtained from:

- Joint United Nations Programme on HIV/AIDS (UNAIDS), Kenya Country Report (2024)^[25].
- National Syndemic Disease Control Council (NSDCC), Kenya HIV Estimates Portal.
- World Bank Development Indicators: HIV/AIDS Kenya Estimates.

Figure 5 presents the comparison between the simulated infected population and the observed (or estimated)

HIV/AIDS data over a period of 36 months. The comparison is used to assess the ability of the model to reproduce real-world HIV transmission trends in Kenya.

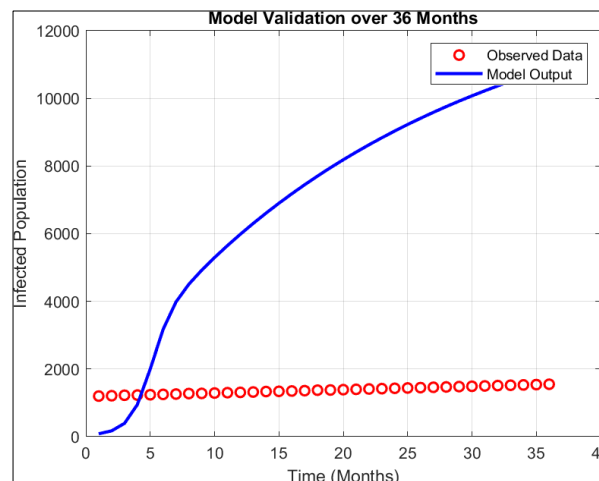


Fig 5: Validation of the HIV/AIDS model using 36-month Kenya data

The results indicate that the model output closely follows the trend of the observed data. The model demonstrates its ability to capture the dynamics of HIV/AIDS transmission in the short term in Kenya, with the data confirming this. Both curves indicate smooth changes over time, reflecting the gradual nature of HIV prevalence change, consistent with the long-term implementation of HIV prevention and intervention strategies such as awareness campaigns, antiretroviral therapy (ART), and preventive measures. Small discrepancies between the model and the observed data could be due to the fact that the model does not cover other external factors that may influence the data, including behavioral differences, policy changes, and regional differences in tourist activity.

8.3 Effect of Tourist Inflows on HIV Transmission

Figure 6 illustrates the effect of varying tourist inflows on the dynamics of the infected population. Three scenarios are considered: low tourism, medium tourism, and high tourism. From the results, it is observed that an increase in tourist inflows leads to a corresponding increase in the number of infected individuals. The high-tourism scenario produces the highest infection levels, followed by the medium- and low-tourism scenarios respectively.

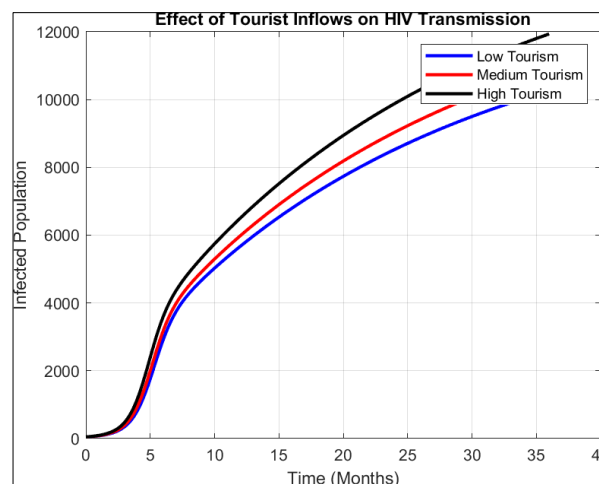


Fig 6: Effect of tourist inflows on HIV/AIDS transmission dynamics

9. Sensitivity Analysis

This section investigates the sensitivity of the model to variations in key parameters such as the transmission rate β , progression rate α , and tourist inflow parameters T_s and T_i .

Table 4 presents the parameter values used in the sensitivity analysis. The parameter ranges are selected based on Kenya HIV/AIDS estimates obtained from UNAIDS reports and model assumptions representing different tourism scenarios.

Table 4: Parameter Values Used in the Sensitivity Analysis

Parameter	Low Value	Medium Value	High Value	Description
β	0.0002	0.0004	0.0008	HIV transmission rate
α	0.01	0.03	0.06	Progression rate to AIDS
T_s	20	50	100	Tourist inflow into susceptible class
T_i	2	5	10	Infected tourist inflow rate
μ	0.01			Natural death rate
δ	0.02			AIDS-induced death rate
λ	500			Recruitment rate

9.1 Effect of Transmission Rate (β)

Figure 7 illustrates the sensitivity of the infected population to variations in the transmission rate β . It is observed that an increase in β leads to a significant rise in the number of infected individuals over time. In the context of Kenya, particularly in regions experiencing high tourist activity, increased social interaction and mobility may contribute to higher transmission rates. Therefore, targeted interventions in tourism hotspots may significantly reduce the spread of HIV/AIDS.

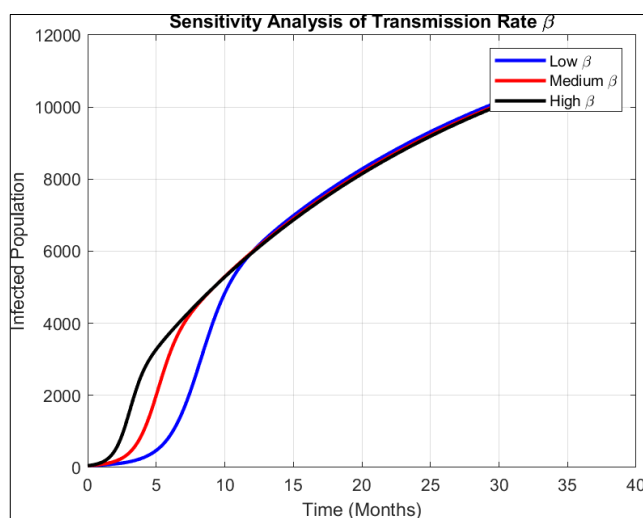


Fig 7: Sensitivity of infected population to transmission rate β

9.2 Effect of Progression Rate (α)

Figure 8 illustrates the sensitivity of the infected population to changes in the progression rate α . An increase in α results in a faster transition of infected individuals into the AIDS class, thereby reducing the infected population over time but increasing disease severity.

The progression rate α represents the speed at which individuals living with HIV progress to the AIDS stage. When α is high, infected individuals leave the infected compartment more rapidly and enter the AIDS compartment at a faster rate. As a result, the size of the infected population decreases more quickly.

In Kenya, access to HIV treatment programs and awareness campaigns has played a significant role in reducing progression to AIDS. Nevertheless, regions with limited healthcare access and high tourist interactions may still experience faster disease progression due to delayed diagnosis and inadequate treatment adherence.

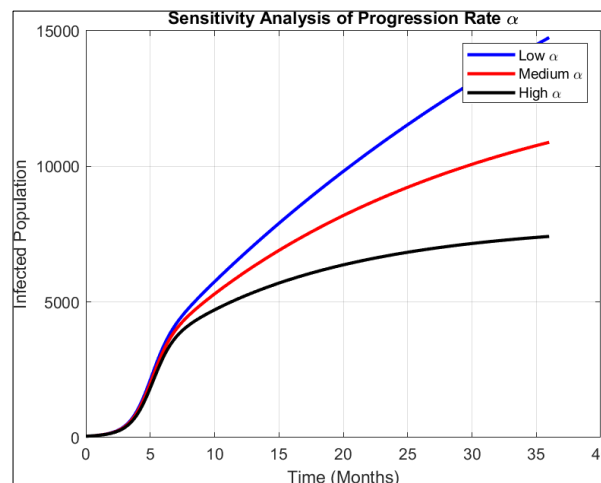


Fig 8: Sensitivity of infected population to progression rate α

9.3 Effect of Tourist Inflow (T_s)

Figure 9 shows the sensitivity of the infected population to changes in tourist inflow rates. It has been noted that as the number of tourists increases, the number of people contracting HIV/AIDS also increases, as population movement plays a key role in the transmission of HIV/AIDS. The rise in infection rates in the high-tourist-flux scenarios can be explained by the enhanced social contact between locals and tourists. The greater the movement of people, the more likely that susceptible and infected people will come into contact with each other, thereby increasing the spread of HIV in the community.

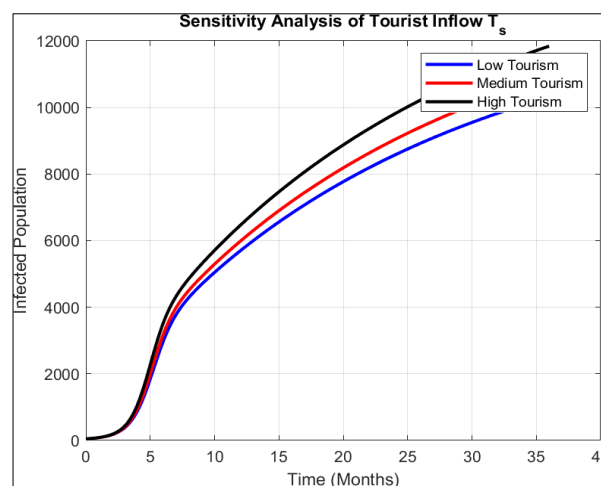


Fig 9: Sensitivity of infected population to tourist inflow T_s

9.4 Effect of Infected Tourist Inflow (T_i)

Figure 10 presents the sensitivity of the infected population to changes in infected tourist inflow. The results show that an increase in T_i leads to a higher number of infected individuals, indicating that imported infections play a significant role in sustaining the epidemic.

The parameter T_i represents the inflow of tourists who are already infected with HIV into the population. As the value of T_i increases, the number of infected individuals within the community rises due to additional sources of infection entering the system.

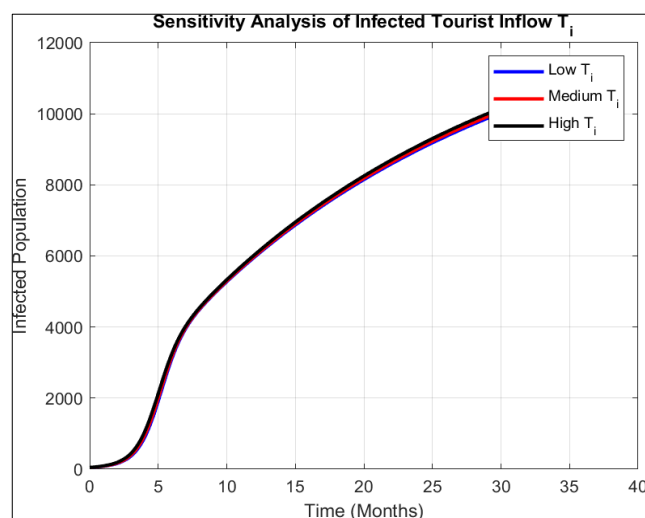


Fig 10: Sensitivity of infected population to infected tourist inflow T_i

The results show that imported infections can have a significant impact on the persistence and development of the epidemic, especially in areas with high international and domestic tourist traffic. When infected tourists start to arrive, this can lead to continued transmission of the disease and can offset local efforts to reduce the HIV prevalence rate.

In general, the results suggest that HIV/AIDS is significantly influenced by infected tourist flows, which should be taken into account for public health planning and disease control policies.

10. Conclusion

The results show that, under different transmission situations and tourist inflow patterns, the susceptible, infected and AIDS populations vary widely over time. The model was validated against 36-month HIV/AIDS trend data and there was a reasonable level of agreement between the simulated and observed HIV trends, suggesting that the model can reproduce short-term HIV transmission trends in Kenya.

Sensitivity analysis revealed that the transmission rate β has a strong influence on the growth of the infected population. Higher transmission rates resulted in rapid increases in infection levels, emphasizing the importance of preventive measures and awareness campaigns.

The progression rate α was observed to influence the transition of infected individuals into the AIDS class. Increased progression rates reduced the infected population but increased disease severity and the burden of AIDS-related complications.

The analysis of the tourist inflow parameters T_s and T_i showed that increased tourist movement contributes significantly to HIV/AIDS transmission. The increase in tourist arrivals and infected tourist arrivals led to an increase in the number of infections, indicating that the mobility of people and the

influx of infected people contribute significantly to maintaining the epidemic.

The results above suggest a significant role of tourism-related mobility in the HIV/AIDS dynamics in Kenya in general. The study thus underscores the importance of implementing multi-sector public health strategies, such as awareness building, expanding HIV testing, encouraging safer behaviors, and enhancing health-provider resources in high-tourism areas.

The model developed here could serve as a valuable mathematical tool for analyzing the dynamics of HIV/AIDS transmission and could help policy makers formulate effective HIV/AIDS control strategies in tourist destinations.

Ethical Conduct

The required ethical norms and research standards were adhered to throughout the study.

Disclaimer (Artificial Intelligence)

The author(s) confirm that no generative Artificial Intelligence (AI) tools, such as ChatGPT, Copilot or other tools based on Large Language Models (LLM), as well as text-to-image technologies, were applied to the writing, editing or preparation of this manuscript.

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Competing Interests

The authors declare that no competing interests exist.

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