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Impact of Defaulter Tracing Strategies on HIV/AIDS Dynamics: A Numerical Simulation Study

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Abstract: Antiretroviral therapy (ART) adherence is crucial for HIV/AIDS control, yet patient default remains a significant challenge. Defaulter tracing aims to re-engage patients lost to follow-up, but its quantitative impact under varying conditions needs assessment. This study employs numerical simulations of a deterministic compartmental HIV/AIDS model to evaluate the impact of varying defaulter tracing effectiveness (DT_{eff}) and ART retention rates (θ) on epidemic dynamics within Kenya. The model, incorporating susceptible, infected, on-ART, not-on-ART, and under-tracing compartments, was solved using the Runge-Kutta-Fehlberg (RKF45) method with parameters informed by data. Scenarios explored DT_{eff} levels from 45% to 75% and retention rates (θ) from 65% to 85%. Simulation results demonstrate that increasing DT_{eff} significantly reduces the untreated infected population (I_{NARV}) and the size of the defaulter population (D_{TR}), while increasing the population maintained on ART (I_{ARV}). However, improving the retention rate (θ) showed a significant impact of reducing the need for tracing and the size of the untreated population, while substantially increasing ART coverage. The findings highlight that while effective defaulter tracing is a vital component, particularly when retention is suboptimal, improving ART retention is fundamental for long-term HIV control. This study shows the need for integrated public health strategies that combine robust, proactive retention efforts with efficient defaulter tracing mechanisms to effectively manage the HIV/AIDS epidemic.

Keywords: HIV/AIDS, Mathematical Model, Defaulter Tracing, Basic Reproduction Number, Stability Analysis

1. Introduction

Human Immunodeficiency Virus/Acquired Immunodeficiency Syndrome (HIV/AIDS) remains a major global health burden, requiring sustained efforts in prevention, treatment, and care [12]. While Antiretroviral Therapy (ART) has transformed HIV into a manageable chronic condition, its long-term success lies on maintaining high levels of treatment adherence [9]. A significant challenge faced by HIV programs worldwide is patient default from ART, where individuals interrupt or cease treatment [1, 10]. Defaulting can lead to severe consequences, including viral rebound, disease progression, the development of drug resistance, and an increased risk of HIV transmission within the community.

Defaulter tracing has emerged as a vital public health intervention designed to address this challenge. It involves systematically identifying, locating, and supporting individuals who have missed scheduled clinic appointments or discontinued ART, with the aim of re-engaging them in care [4, 6]. Effective defaulter tracing can improve retention in care, enhance treatment adherence and ultimately contribute to better health outcomes for individuals and the community.

Despite the recognized importance of defaulter tracing, there is a need for a deeper quantitative understanding of how different tracing strategies impact HIV epidemic dynamics, particularly concerning variations in tracing effectiveness and its interaction with overall retention program [3]. Evaluating the effectiveness of defaulter tracing interventions is essential for optimizing resource allocation and designing evidence-based control programs. While empirical studies exist [4],

mathematical modeling and numerical simulation provide powerful tools to explore complex dynamics and compare the potential impact of different intervention scenarios over time [2].

The goal of this study is to assess the potential impact of defaulter tracing effectiveness and ART retention strategies on achieving HIV/AIDS epidemic control. To achieve this, the study aims to numerically simulate an HIV/AIDS mathematical model to evaluate how varying levels of defaulter tracing effectiveness influence key epidemic indicators. Furthermore, it seeks to quantify the impact of different ART retention rates on the dynamics of the HIV-infected population, both on and off treatment, and to explore the combined effect of defaulter tracing effectiveness and ART retention on population subgroups relevant to epidemic control, such as those on ART, not on ART, and individuals under tracing.

The investigation employs a compartmental mathematical model which divides the population into susceptible, infected, infected on ART, infected not on ART, and defaulters under tracing compartments.

2. Methodology

This section details the methods employed in the numerical simulation study to assess the impact of defaulter tracing strategies on HIV/AIDS dynamics.

2.1. Mathematical Model

The simulation study utilizes a deterministic compartmental mathematical model representing the transmission dynamics of HIV/AIDS, incorporating treatment and defaulter tracing. The model divides the total population into five compartments: Susceptible (S_p), Infected (I_T), Infected receiving Antiretroviral Therapy (I_{ARV}), Infected but not receiving ART (I_{NARV}), and individuals previously on ART who have defaulted and are currently under Defaulter Tracing (D_{TR}). The flow between these compartments is governed by parameters representing infection, treatment initiation, defaulting from treatment, natural mortality, disease-induced mortality, and the processes of tracing and re-engagement into care as shown in Figure 1.

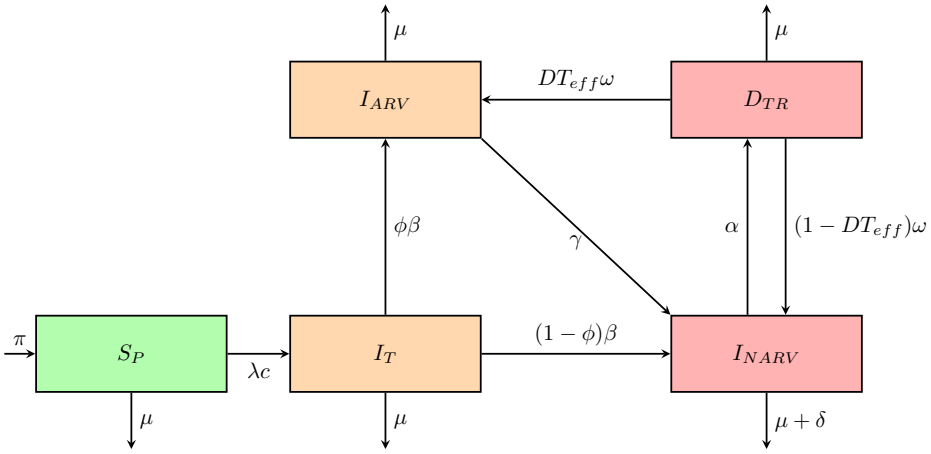

Figure 1. *Flow diagram of the HIV/AIDS model with defaulter tracing. Arrows indicate the transition of individuals between compartments S_p (Susceptible), I_T (Infected Total/Initial), I_{ARV} (Infected on ART), I_{NARV} (Infected not on ART), and D_{TR} (Defaulters under Tracing). Parameters governing the transitions are shown alongside the arrows.*

The dynamics of the system are described by the following system of ordinary differential equations (ODEs), derived from the flow diagram depicted in Figure 1:

$$\begin{aligned}
\frac{dS_p}{dt} &= \pi N - \frac{\lambda c S_p I_T}{N} - \mu S_p \\
\frac{dI_T}{dt} &= \frac{\lambda c S_p I_T}{N} - (\beta + \mu) I_T \\
\frac{dI_{ARV}}{dt} &= \phi\beta I_T - (\gamma + \mu) I_{ARV} + DT_{eff}\omega D_{TR} \\
\frac{dI_{NARV}}{dt} &= (1-\phi)\beta I_T + \gamma I_{ARV} - (\alpha + \mu + \delta) I_{NARV} + (1 - DT_{eff})\omega D_{TR} \\
\frac{dD_{TR}}{dt} &= \alpha I_{NARV} - (\omega + \mu) D_{TR}
\end{aligned} \tag{1}$$

Here, the parameters ($\pi, \lambda, c, \mu, \beta, \phi, \gamma, \alpha, \delta, DT_{eff}$) represent various epidemiological and intervention rates as defined in Table 1.

2.2. Numerical Simulation Setup

2.2.1. Numerical Method

The system of ordinary differential equations (ODEs) (1) describing the HIV/AIDS dynamics was solved numerically using the Runge-Kutta-Fehlberg (RKF45) method. This method is well-suited for solving systems of ODEs, particularly when adaptive step-size control is beneficial for maintaining accuracy and efficiency, as is often the case in modeling epidemiological dynamics.

The RKF45 method combines a fourth-order Runge-Kutta method with a fifth-order Runge-Kutta method to estimate the solution and the local truncation error at each step. Let y_n be the numerical approximation of the solution vector $y(t)$ at time t_n, and let h be the step size. The formulas for advancing from t_n to $t_{n+1} = t_n + h$ involve calculating several intermediate stages (K_i):

$$K_1 = hf(t_n, y_n) \tag{2}$$

$$K_2 = hf\left(t_n + \frac{1}{4}h, y_n + \frac{1}{4}K_1\right) \tag{3}$$

$$K_3 = hf\left(t_n + \frac{3}{8}h, y_n + \frac{3}{32}K_1 + \frac{9}{32}K_2\right) \tag{4}$$

$$K_4 = hf\left(t_n + \frac{12}{13}h, y_n + \frac{1933}{2197}K_1 - \frac{7200}{2197}K_2 + \frac{7296}{2197}K_3\right) \tag{5}$$

$$K_5 = hf\left(t_n + h, y_n + \frac{439}{216}K_1 - 8K_2 + \frac{3680}{513}K_3 - \frac{845}{4104}K_4\right) \tag{6}$$

$$K_6 = hf\left(t_n + \frac{1}{2}h, y_n - \frac{8}{27}K_1 + 2K_2 - \frac{3544}{2565}K_3 + \frac{1859}{4104}K_4 - \frac{11}{40}K_5\right) \tag{7}$$

Such that the fifth-order approximation (y_{n+1}) and the fourth-order approximation (z_{n+1}) are given below:

$$y_{n+1} = y_n + \frac{25}{216}K_1 + \frac{1408}{2565}K_3 + \frac{2197}{4104}K_4 - \frac{1}{5}K_5 \tag{8}$$

$$z_{n+1} = y_n + \frac{16}{135}K_1 + \frac{6656}{12825}K_3 + \frac{28561}{56430}K_4 - \frac{9}{50}K_5 + \frac{2}{55}K_6 \tag{9}$$

The difference $|y_{n+1} - z_{n+1}|$ provides an estimate of the local error. This error estimate is used to adjust the step size h dynamically, ensuring that the error remains within a specified tolerance level throughout the simulation. Numerical simulations were implemented using MATLAB.

2.2.2. Parameter Values and Initial Conditions

The simulations were initialized using population data relevant to Kenya, particularly focusing on the 15–64 age group.

1. The total population at risk (age 15–64) was estimated at 52 million [12]. We thus set the initial susceptible population $S_p(0) = 52,000,000$.
2. According to [8], the people living with HIV (PLHIV) are estimated to be 1.6 million. Thus, we set $I_T(0) = 1,600,000$.
3. Out of the PLHIV population, approximately 1.338 million were estimated to be on ART [12], thus $I_{ARV}(0) = 1,338,000$.
4. This implies the initial population infected but not on ART is $I_{NARV}(0) = I_T(0) - I_{ARV}(0) = 1,600,000 - 1,338,000 = 262,000$.
5. Defaulter tracing was assumed to be initially ineffective or not fully established, which is consistent with challenges noted in [4, 10], hence $D_{TR}(0) = 0$.

The baseline parameter values used for the simulations are listed in Table 1, derived from literature, reports, and assumptions.

Table 1. *Baseline Parameter Values for Numerical Simulation.*

Parameter	Description	Value	Source
π	Recruitment (persons/year)	5250	[11]
β	Rate at which infected use ARTs	0.0015	Assumed
α	Tracing rate of defaulted persons	0.0055	Assumed
δ	HIV-related death rate	3.45×10^{-5}	[12]
ϕ	Proportion defaulting medication	0.75	[12]

Parameter	Description	Value	Source
μ	Natural death rate	3.56×10^{-4}	[11]
c	Effective contact rate	3.72×10^{-4}	Assumed
γ	Rate of dropping out of care	3.76×10^{-4}	[5]
θ	Rate of retention on ARV	$[0.65 - 0.85]$	Assumed
DT_{eff}	Defaulter tracing effectiveness	$[0.45 - 0.75]$	Assumed
ω	Awareness campaigns for ART uptake	0.005	Assumed

The parameters varied in the simulation scenarios are the defaulter tracing effectiveness, DT_{eff}, and the ART retention rate, θ. The retention rate θ determines the rate of dropping out of care γ via the relationship $\gamma = (1-\theta)\phi\beta$.

2.2.3. Simulation Scenarios

To evaluate the impact of key interventions on HIV/AIDS dynamics, several simulation scenarios were conducted by varying specific model parameters, while keeping others at their baseline values (Table 1). The simulations focused on the effects of defaulter tracing effectiveness (DT_{eff}) and ART retention rate (θ).

Scenario 1: Varying Defaulter Tracing Effectiveness (DT_{eff}) In this set of simulations, the effectiveness of the defaulter tracing program was varied to assess its impact on the population dynamics. The baseline parameter values were used, except for DT_{eff}, which was set to three different levels representing low, moderate, and high effectiveness:

1. Low effectiveness: $DT_{eff} = 0.45$ (45%)
2. Moderate effectiveness: $DT_{eff} = 0.60$ (60%)
3. High effectiveness: $DT_{eff} = 0.75$ (75%)

The results of these simulations are presented to show the dynamics of the traced defaulter population (D_{TR}), the population on ART (I_{ARV}), and the population infected but not on ART (I_{NARV}) over the simulation period.

Scenario 2: Varying Retention Rate (θ) This set of simulations explored the impact of the ART retention rate (θ) on the epidemic dynamics. The retention rate directly influences the rate at which individuals abandon ART (γ), calculated as $\gamma = (1-\theta)\phi\beta$. Three levels of retention were simulated:

1. Low retention: $\theta = 0.65$ (65%)
2. Moderate retention: $\theta = 0.75$ (75%)
3. High retention: $\theta = 0.85$ (85%)

All other parameters were kept at their baseline values. The simulations illustrate how different retention levels affect the size of the defaulter population requiring tracing (D_{TR}), the population successfully maintained on ART (I_{ARV}), and the population infected but not on ART (I_{NARV}).

All simulations were run for a period of 1800 days, equivalent to approximately 5 years, to observe both short-term and medium-term dynamics of the interventions.

3. Results

This section presents the results obtained from the numerical simulations of the HIV/AIDS model (1) under different scenarios of defaulter tracing effectiveness (DT_{eff}) and ART retention rate (θ).

3.1. Impact of Defaulter Tracing Effectiveness (DT_{eff})

The following figures illustrate the dynamics of the D_{TR} populations over 1800 days when varying the effectiveness of defaulter tracing (DT_{eff} = 45%, 60%, 75%).

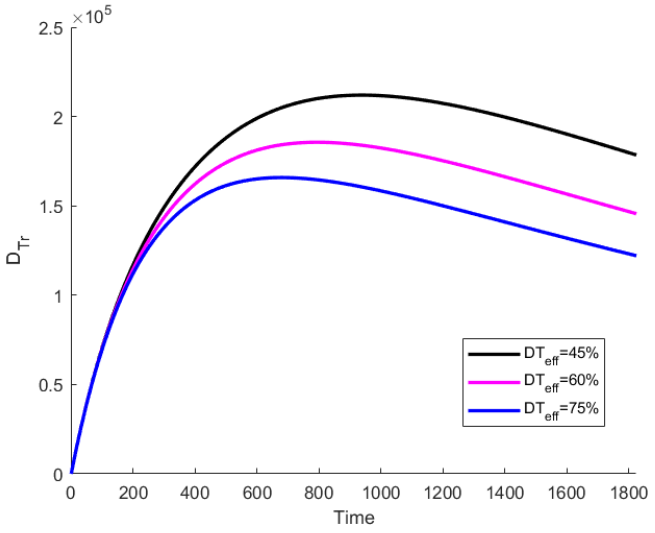

Figure 2. *Defaulter Tracing Population (D_{TR}) over Time for Varying DT_{eff}.*

Figure 2 shows the number of individuals in the defaulter tracing population (D_{TR}) over time. Initially, the number of defaulters being traced increases rapidly as ART programs identify individuals who have defaulted. The peak number of individuals under tracing is higher and occurs later when tracing effectiveness is lower ($DT_{eff} = 45\%$), as inefficient tracing allows defaulters to accumulate. Conversely, higher tracing effectiveness ($DT_{eff} = 75\%$) leads to a lower peak and a faster decline, indicating that individuals are being successfully returned to ART more quickly, reducing the size of the defaulter population.

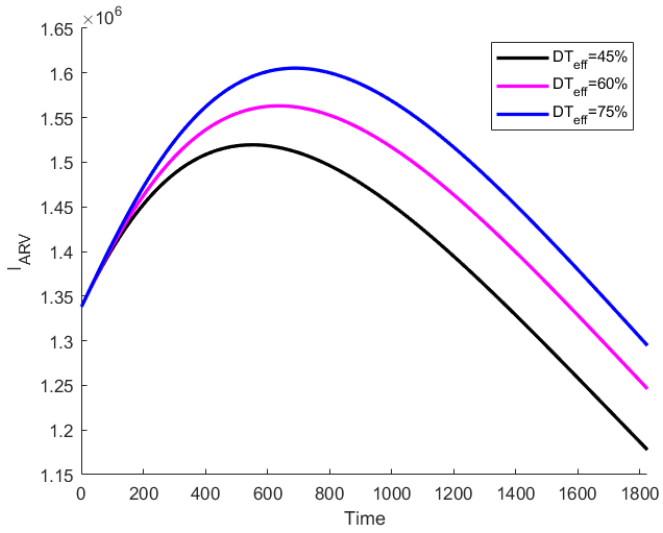

Figure 3. *Population under ART (I_{ARV}) over Time for Varying DT_{eff}.*

Figure 3 illustrates the impact of tracing effectiveness on the population receiving ART (I_{ARV}). Higher tracing effectiveness ($DT_{eff} = 75\%$) results in a larger number of individuals maintained on ART over the simulation period compared to lower effectiveness levels. This is because more effective tracing successfully re-engages defaulters, preventing sustained treatment interruptions and contributing to higher overall retention in the ART program. Lower tracing effectiveness ($DT_{eff} = 45\%$) leads to a smaller peak and a faster decline in the I_{ARV} population due to higher dropout rates not being adequately compensated by tracing efforts.

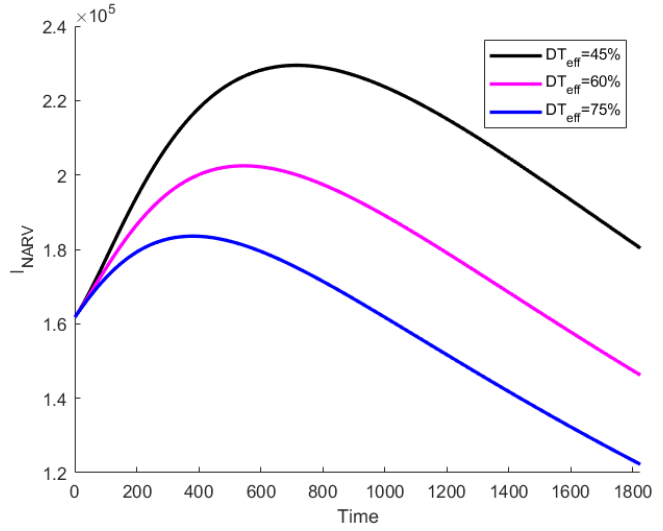

Figure 4. *Population Not under ART (I_{NARV}) over Time for Varying DT_{eff}.*

Figure 4 shows the dynamics of the population infected with HIV but not currently receiving ART (I_{NARV}). Increased tracing effectiveness leads to a lower peak and a more rapid decline in the I_{NARV} population. When $DT_{eff} = 75\%$, more defaulters are successfully traced and returned to care (moving out of D_{TR} to I_{ARV}), thus reducing the number of individuals contributing to the I_{NARV} population (either directly or indirectly via γ). Lower effectiveness ($DT_{eff} = 45\%$) results in a higher peak and slower decline of I_{NARV}, indicating a larger population of untreated individuals who pose a risk for further transmission and disease progression.

3.2. Relationship Between Untraced and Traced Populations

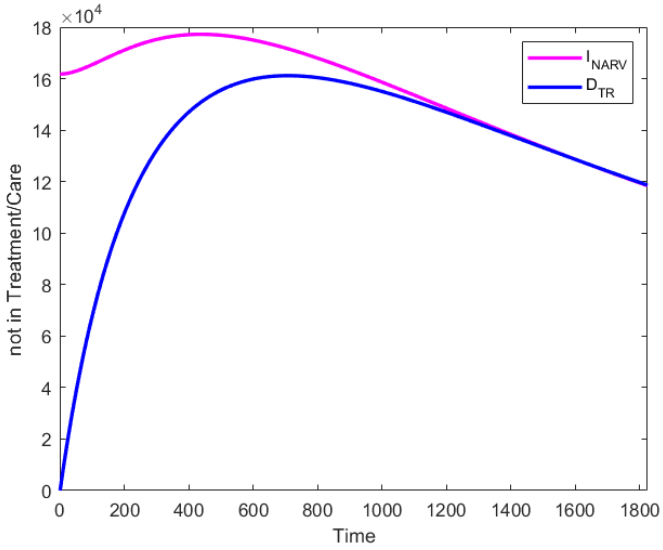

Figure 5. *Dynamics of Population Not under ART (I_{NARV}) and Population under Defaulter Tracing (D_{TR}) over Time (Baseline Scenario).*

Figure 5 compares the dynamics of the population not under ART (I_{NARV}) and the population actively being traced (D_{TR}). Initially, both populations increase. The I_{NARV} curve peaks earlier and then declines, while the D_{TR} curve rises sharply as tracing efforts intensify and then stabilizes before declining. The subsequent decline in I_{NARV} is influenced by the effectiveness of tracing (transferring individuals from D_{TR} back to I_{ARV}) and treatment initiation. The merging trends suggest that, over time, a significant portion of the untreated population is captured by the tracing system. This highlights the potential effectiveness of tracing and reintegration strategies in reducing the overall population of untreated HIV infections.

3.3. Impact of Retention Rate (θ)

The following figures show the effect of varying the ART retention rate (θ = 65%, 75%, 85%) on the different population compartments. Recall that $\gamma = (1 - \theta)\phi\beta$.

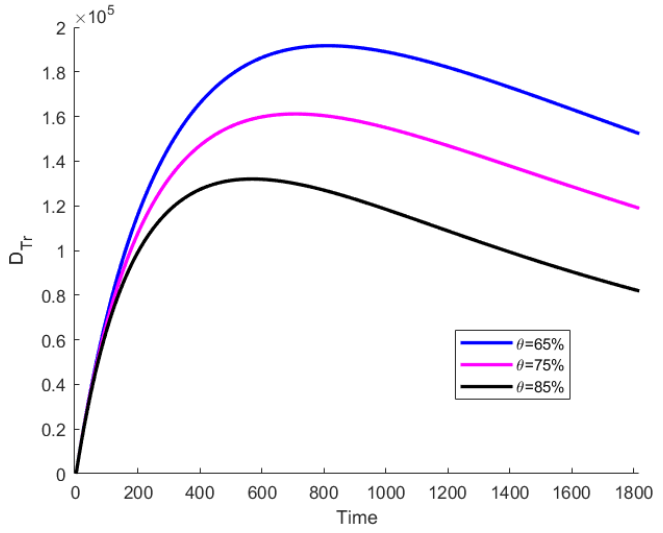

Figure 6. *Defaulter Tracing Population (D_{TR}) over Time for Varying Retention Rate θ.*

Figure 6 demonstrates how the ART retention rate affects the number of individuals needing tracing (D_{TR}). At a low retention rate ($\theta = 65\%$), more individuals default from ART, leading to a larger number entering the tracing population, resulting in a higher peak for D_{TR}. As the retention rate improves ($\theta = 75\%$ and $\theta = 85\%$), fewer individuals default, significantly reducing the number requiring tracing. With high retention ($\theta = 85\%$), the D_{TR} population remains low throughout the simulation, indicating that proactive retention minimizes the need for reactive tracing.

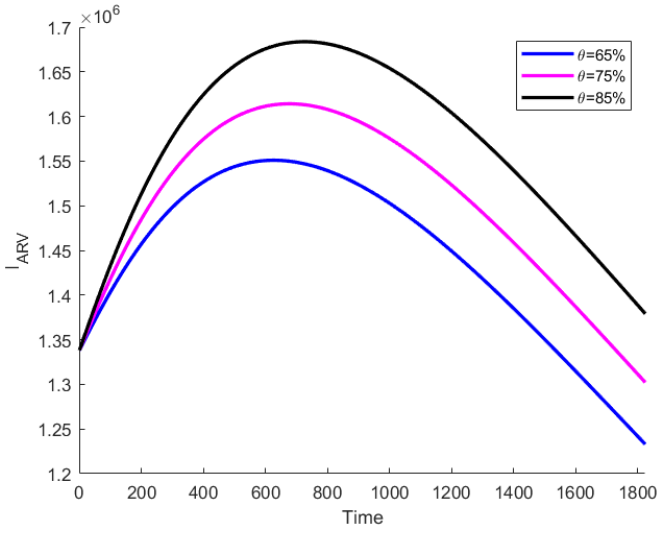

Figure 7. *Population under ART (I_{ARV}) over Time for Varying Retention Rate θ.*

Figure 7 shows the impact of retention rate on the population actively receiving ART (I_{ARV}). Higher retention rates ($\theta = 85\%$) lead to a significantly larger and more sustained population on ART compared to lower retention rates ($\theta = 65\%$). Improved retention directly translates to better treatment coverage and stability within the ART program. While all scenarios show an eventual decline (potentially due to mortality exceeding recruitment into ART over the long term), higher retention significantly delays and mitigates this decline.

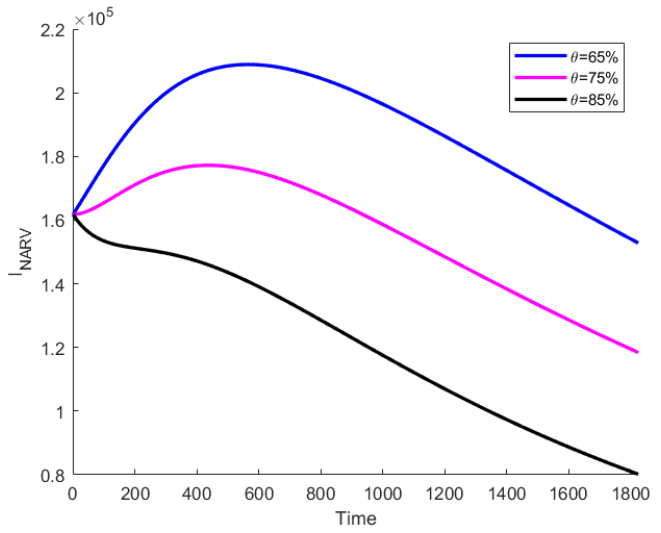

Figure 8. *Population Not under ART (I_{NARV}) over Time for Varying Retention Rate θ.*

Figure 8 illustrates the effect of retention on the population infected but not receiving ART (I_{NARV}). At low retention ($\theta = 65\%$), the I_{NARV} population peaks at a high level and declines slowly, as many individuals drop out of treatment. Increasing the retention rate to 75% and further to 85% significantly reduces the peak size and accelerates the decline of the I_{NARV} population. With high retention ($\theta = 85\%$), the number of untreated individuals decreases almost immediately, demonstrating the powerful effect of sustained ART adherence in controlling the untreated, infectious population.

3.4. Sensitivity of Parameters (Numerical Evaluation)

To complement the simulation results and identify parameters with a strong influence on the epidemic potential under the specific baseline conditions used, Table 2 presents numerically evaluated sensitivity indices for the basic reproduction number (R_0). These indices were calculated using the baseline parameter values from Table 1.

Table 2. *Numerically Evaluated Sensitivity Indices of R_0.*

Parameter	Sensitivity Index ($\Upsilon_P^{R_0}$)
π (Recruitment rate)	1.0000
β (ART use rate)	4.62×10^{-7}
α (Defaulter tracing rate)	-1.0001
δ (HIV-related death rate)	8.36×10^{-6}
ϕ (Medication default rate)	0.0000
μ (Natural death rate)	7.81×10^{-4}
λ (Probability of infection)	1.0000
c (Contact rate of infection)	1.0000
ω (Rate of return of defaulters)	0.0000
γ (Proportion/rate of defaulters)	7.34×10^{-4}

Based on the numerical values presented in Table 2 (from the source document), the parameters with a sensitivity index magnitude of 1 (π, λ, c, α) appear to be the most influential on the calculated R_0. The positive indices for recruitment and transmission parameters (π, λ, c) confirm their role in driving the epidemic. The large negative index for the tracing initiation rate (α) suggests that, under the assumptions leading to this numerical result, increasing the rate at which non-ART individuals are identified for tracing significantly reduces R_0. The other parameters, including ART initiation rate (β), mortality rates (δ, μ), and ART drop out rate (γ), show very small indices in this numerical evaluation.

4. Discussion

The numerical simulations conducted in this study provide quantitative insights into the impact of defaulter tracing effectiveness (DT_{eff}) and ART retention rate (θ) on the dynamics of HIV/AIDS within the modeled population, representing the context of Kenya.

Impact of Defaulter Tracing Effectiveness: The results clearly demonstrate that increasing the effectiveness of defaulter tracing significantly improves HIV control outcomes. As shown in Figures 2, 3, and 4, higher tracing effectiveness (e.g., $DT_{eff} = 75\%$) leads to:

1. A smaller peak and faster resolution of the defaulter population (D_{TR}), indicating efficient re-engagement.
2. A higher and more sustained number of individuals maintained on ART (I_{ARV}), reflecting improved treatment coverage.
3. A lower peak and faster decline in the number of individuals infected but not on ART (I_{NARV}), signifying reduced untreated prevalence and lower transmission potential.

Conversely, low tracing effectiveness ($DT_{eff} = 45\%$) allows the defaulter population to grow larger, diminishes the number of people successfully retained on ART, and sustains a larger population of untreated individuals for longer periods. This indicates that robust tracing mechanisms are crucial for mitigating the negative consequences of treatment interruption. Figure 5 further highlights the interplay, showing how effective tracing efforts (D_{TR}) directly contribute to reducing the untreated population (I_{NARV}) over time.

Impact of Retention Rate: The simulations varying the retention rate (θ) reveal its profound impact on HIV dynamics (Figures 6, 7, 8). Improving retention from 65% to 85% results in:

1. A significant reduction in the number of individuals defaulting and needing tracing (D_{TR}). High retention proactively prevents defaults, lessening the burden on tracing systems.
2. A substantial increase in the number of individuals successfully maintained on ART (I_{ARV}), leading to better long-term viral suppression at the population level.
3. A significant reduction and faster decline in the untreated population (I_{NARV}). High retention minimizes the population of individuals who are not virally suppressed and can transmit the virus.

These findings emphasize that strategies aimed at improving ART adherence and retention are fundamental to achieving long-term HIV epidemic control. Even with effective tracing, poor retention leads to a persistently high number of untreated cases and a large tracing workload.

The results suggest an important interaction between tracing and retention. At lower retention rates, effective defaulter tracing plays a critical role in mitigating the damage by returning individuals to care. However, as retention improves, the reliance on tracing diminishes, allowing resources to potentially be shifted towards maintaining high retention and other prevention efforts. A well-structured HIV control program should therefore integrate both proactive retention strategies (counseling, support groups, addressing barriers) and efficient reactive defaulter tracing mechanisms. The simulations indicate that combining high retention (e.g., 85%) with effective tracing would yield the most significant reductions in untreated HIV prevalence and maximize the population benefiting from ART.

Public health policies should therefore prioritize a dual approach: strengthening systems to keep patients on ART while also implementing efficient tracing systems to recover those who inevitably drop out of care [7, 12].

5. Conclusion

This study utilized numerical simulations of a compartmental HIV/AIDS model to quantitatively evaluate the impact of defaulter tracing effectiveness (DT_{eff}) and ART retention rates (θ) on controlling the HIV epidemic in Kenya. The simulations provide valuable insights into how these interventions shape the dynamics of different population subgroups over time.

The key findings from the simulations reinforce the importance of both defaulter tracing and retention strategies. Our results demonstrate that:

1. *Effective defaulter tracing significantly mitigates the negative impact of ART default.* Increasing tracing effectiveness (DT_{eff}) leads to a quantifiable reduction in the untreated HIV-positive population (I_{NARV}) and the size of the defaulter population (D_{TR}), while concurrently increasing the number of individuals successfully maintained on ART (I_{ARV}). This highlights defaulter tracing as a vital tool for improving treatment coverage and reducing transmission potential, particularly in the earlier phases of ART dropout.
2. *Improving ART retention has a profound and arguably more fundamental impact on epidemic control.* Higher retention rates (θ) significantly reduce the number of individuals defaulting and requiring tracing (D_{TR}), substantially increase the population benefiting from sustained ART (I_{ARV}), and lead to a faster and more significant decline in the untreated, infectious

population (I_{NARV}). This signifies that proactive measures to keep individuals engaged in care are crucial for long-term HIV suppression.

3. *Tracing and retention strategies are complementary.* While high retention minimizes the need for tracing, effective tracing provides an essential support for individuals who default, especially when retention rates are suboptimal. A combination of high retention and effective tracing yields the best outcomes in reducing the untreated HIV burden.

These findings confirm that defaulter tracing, when implemented effectively, serves as a crucial intervention for HIV/AIDS control by reducing the population of untreated individuals and supporting sustained treatment engagement. However, the simulations strongly suggest that prioritizing and enhancing ART retention strategies is paramount for achieving efficient and sustainable long-term epidemic control.

In conclusion, this numerical study quantitatively demonstrates the significant positive impact of both effective defaulter tracing and high ART retention on controlling HIV spread. By guiding investments in these complementary strategies, public health programs can accelerate progress towards achieving HIV epidemic control goals.

6. Recommendations

Based on the simulation results attained in this study, the following policy and programmatic recommendations are proposed to enhance HIV/AIDS epidemic control:

1. *Strengthen and Scale Up Defaulter Tracing Programs:* Health systems should invest in and strengthen proactive defaulter tracing programs. This includes utilizing effective mechanisms such as community health workers, digital health tools (e.g., SMS reminders, mHealth apps), and routine monitoring systems to promptly identify and re-engage individuals who have defaulted from ART [3, 6].
2. *Prioritize and Enhance ART Retention Strategies:* A strong emphasis must be placed on improving ART retention through comprehensive, patient-centered strategies. These should include enhanced counseling, robust peer support programs, proactive measures to address socio-economic barriers to adherence (e.g., transportation, food security), and the implementation of differentiated service delivery models tailored to patient needs [7].
3. *Foster an Integrated Approach:* An integrated approach that combines robust retention initiatives with efficient and responsive tracing systems is likely to be the most effective strategy for maximizing ART coverage, minimizing treatment interruptions, and ultimately reducing HIV transmission. These two prongs should not be seen as mutually exclusive but as synergistic components of HIV care.
4. *Utilize Data-Driven Decision Making for Resource Allocation:* Mathematical modeling and simulation, informed by real-time programmatic data and local surveillance, should be continuously utilized to optimize the allocation of resources between retention and tracing activities. This can help tailor interventions based on specific contexts, program performance, and evolving epidemic dynamics.
5. *Invest in Research for Effective Tracing Modalities:* Further operational research is valuable to assess and identify the most cost-effective and impactful defaulter tracing modalities in different settings, considering factors like population density, mobility, and available infrastructure.

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Abbreviations

AIDS	Acquired Immuno-Defficiency Syndrome
ART	Anti-Retroviral Therapy
HIV	Human Immuno-deficiency Virus
MATLAB	MATRIX LABoratory
ODEs	Ordinary Differential Equations
PLHIV	People Living with HIV

Conflicts of Interest

The authors declare no conflicts of interest.

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