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A study of trend and pattern of HIV/AIDS disease in India using growth curve models

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Abstract

This study aims to explore the trends and patterns of HIV/AIDS disease prevalence in India by employing statistical growth curve models. Over the period 2000 to 2021, India has witnessed significant shifts in HIV/AIDS incidence, prevalence, and mortality. The analysis utilizes data sourced from National Aids Control Organization (NACO), focusing on key statistical metrics such as incidence rates, prevalence rates, and mortality of HIV/AIDS in India. The study applies various growth models, including Exponential growth, Logarithmic growth, and Polynomial growth models, to analyze the temporal dynamics and were fitted to capture the trends more accurately. Growth rates, including exponential growth rates, are computed to understand the speed of the epidemic's expansion or contraction across different years. These models help to identify regions with the highest burden and the effectiveness of control measures, such as antiretroviral therapy (ART), in mitigating the disease's impact. By comparing model outputs with actual observed data, the study provides insights into the trajectory of HIV/AIDS in India, its regional disparities, and the potential for future interventions. The findings reveal that a significant reduction in HIV/AIDS incidence, prevalence and mortality rates in recent years, The Exponential growth model was most accurate for incidence and prevalence trends, while the Polynomial growth model best captured mortality trends based on bias and accuracy tests, the study will contribute to a more nuanced understanding of the epidemic's progression and inform targeted policy and healthcare strategies to curb HIV transmission across the country.

Keywords: HIV/AIDS, growth curve models, incidence rate, prevalence rate, mortality rate

1. Introduction

Human life is surrounded by many ugly deadly diseases and some of them are only prevention without cure and one among them is Human Immunodeficiency Virus (HIV). HIV is a virus that takes over certain immune system cells to make many copies of it. HIV causes slow but constant damage to the immune system. AIDS stands for Acquired Immune Deficiency Syndrome. AIDS is the condition diagnosed when there are a group of related symptoms that are caused by severe HIV infection or in layman's term AIDS is the latter stage of HIV.

HIV is transmitted through four body fluids: blood, semen, vaginal fluid, and breast milk. In order to pass HIV from one person to another, HIV-infected fluid from one person needs to get into the bloodstream of another person. HIV is usually transmitted through sharing needles, unprotected anal, vaginal, and sometimes oral sex, and from mother to infant before or during delivery or while breastfeeding.

Estimated HIV prevalence of adults in the age group between 15-49 years has declined in India. Epidemic was very high in 2000 that is it is 0.55% in 2000 and it is declined to 0.32% in 2010 and 0.21 in 2022. The state wise HIV prevalence in India shows the highest prevalence is observed in northeast region, the state Mizoram (2.70%), 1.36% in Nagaland and 1.05% in Manipur followed by Southern states namely Andhra Pradesh (0.67%), Telangana (0.47%) and Karnataka (0.46%). In India, the estimated number of People Leaving with HIV (PLHIV) is 24 lakhs. The highest number of PLHIV is in southern states namely Maharashtra, Andhra Pradesh and Karnataka. In India the estimated Annual New Infection (ANI) are nearly 62,970 in 2021, around 46.3% decline in ANI at National level in 11 years (2010-2021).

Declining trend is observed in most of the states. Rapid decline from 2010-2021 in three states viz. Himachal Pradesh(73%), Tamil Nadu (72%) and Telangana (71%) and increasing trend is estimated in Northeastern states-Tripura, Meghalaya, Arunachal Pradesh, Assam, Sikkim, Mizoram, and the Union Territory of Dadra and Nagar Haveli and Daman and Diu. There are 41970 estimated AIDS related deaths in India in 2021. A decline of 76.5% AIDS deaths from 2010-21. The declining trend is observed in all States/UTs excluding Puducherry, Arunachal Pradesh, Meghalaya, and Tripura. The highest decline in AIDS-related death (ARD) is estimated in Chandigarh, Telangana, and West Bengal. Prevention of mother-to-child transmission of HIV (PMTCT) need are estimated at 20,612 in 2021 in India. Top 3 states accounting for the highest need are Maharashtra (12.9%), Bihar (11.9%) and Uttar Pradesh (10.6%) (NACO, (2022))^[1].

In this paper an analysis of the trend and pattern of morality of HIV/AIDS disease with indicators like prevalence rate, incidence rate and deaths (in lakhs) in India in the specified duration 2000-2021 is considered. This paper consists of five sections: Introduction about the study is given in the first section, second section deals with review of literature, methods and materials is given in third section, forth section contains Results and discussions of data and final section concludes the study.

India has one of the largest HIV/AIDS populations globally, making it essential to track mortality trends to assess public health interventions. In the epidemic's early stages (1980s-early 1990s), HIV spread rapidly among high-risk groups like sex workers, IDUs, and MSM due to limited awareness and healthcare infrastructure, raising mortality rates. (Panikar, 1992)^[2]. NACO (1995)^[3] later emphasized the need for a national program. ART introduction under the National AIDS Control Programme in 2004 helped reduce mortality, though challenges like late diagnosis persisted Basu *et al.* (2006)^[4]; Lanjewar (2007)^[5]. Jha *et al.* (2007)^[6] noted regional disparities in HIV/AIDS mortality, with southern states like Tamil Nadu and Andhra Pradesh seeing declines due to better healthcare, while northern states struggled with rising deaths from limited ART access and stigma. Solomon *et al.* (2008)^[7] reported significant mortality declines in Tamil Nadu, aided by strong public health support. John *et al.* (2014)^[8] found similar declines in Karnataka's urban areas, though rural areas still faced higher mortality due to limited healthcare and stigma.

Growth models are crucial for tracking the HIV/AIDS epidemic, forecasting trends, and guiding policy. These models, ranging from simple exponential or logistic to complex compartmental forms, depict how HIV/AIDS cases evolve over time. In the early epidemic in India, exponential models predicted a rapid rise in cases due to limited awareness and treatment. Mann *et al.* (1992)^[9] used this model to warn of uncontrolled spread without intervention, while Godbole and Mehendale (2005)^[10] showed that as public health measures improved, exponential models began overestimating long-term trends.

Kumar *et al.* (2008)^[11] used a logistic growth model to project HIV in India, while Gupta *et al.* (2012)^[12] extended it to show slowing growth in high-prevalence states like Maharashtra due to ART and prevention efforts. Sharma and Narain (2017)^[13] applied the Gompertz model, highlighting regional differences in prevalence decline. For short-term projections, Tripathi *et al.* (2013)^[14] used a polynomial model to capture fluctuations in incidence but noted its limitations

for long-term forecasts. Desai *et al.* (2014)^[15] explored non-linear models to account for erratic incidence patterns in specific regions. Patel *et al.* (2019)^[16] enhanced HIV incidence predictions in India by integrating machine learning with logistic growth models, showing that real-time ART and risk behaviour data improved accuracy. Rani *et al.* (2021)^[17] combined the Gompertz model with socioeconomic data to project the impact of future public health interventions on the epidemic.

2. Methods and Materials

The data on prevalence rate, incidence rate and deaths (in lakhs) due to HIV/AIDS disease is collected from NACO for India in the form of time series data from 2000 to 2021. NACO (2021)^[18] Exponential, Logarithmic and Polynomial Growth models and Growth rates are used to study the trend and pattern behaviour of HIV/AIDS disease. Growth models are used to describe and predict how a particular quantity changes over time. They are widely applied in various fields, including Epidemiology, Economics, Biology, and Sociology. In the context of disease prevalence, incidence, and mortality rates (like for HIV/AIDS), growth models help to analyze trends and forecast future behaviour. For our study we applied the models viz. Exponential growth model, Logarithmic growth model and Polynomial of order 3 to fit the data on prevalence rates, incidence rate, and mortality.

Growth rates: Growth rates are key metrics used to measure how quickly or slowly a quantity (e.g., population, disease prevalence, economic output) changes over time. In the context of epidemiology and public health, growth rates are essential for understanding the spread of diseases such as HIV/AIDS. Here is an overview of exponential growth rate and growth models used in our study:

2.1 Exponential Growth Rate

$$\text{Exponential growth rate } (r) = \frac{1}{t} \times \ln \left(\frac{P_t}{P_0} \right) \times 100$$

2.2 Exponential Growth Model: The general equation for exponential growth model is

$$y(t) = y_0 e^{rt}$$

where:

- $y(t)$ is the value of the quantity at time t .
- y_0 is the initial quantity at time $t=0$.
- r is the decay constant, which represents the rate of decay.
- t is the time.

2.3 Logarithmic Growth Model: The general form of a logarithmic growth model is:

$$y = a + b \cdot \ln(t)$$

where:

- y represents the dependent variable (e.g., mortality rate or case count),
- t is the independent variable (e.g., time or a relevant predictor),
- a and b are constants,
- $\ln(t)$ is the natural logarithm of t .

2.4 Polynomial of order 3 (Cubic Polynomial Model): The general form of a cubic polynomial model is:

$$Y = b_0 + b_1 \times t + b_2 \times t^2 + b_3 \times t^3$$

where:

- Y is the dependent variable at time t,
- t is time (e.g., in years),
- $b_0, b_1, b_2,$ and b_3 are the coefficients to be estimated.

3. Results and Discussions

3.1 Growth Rate of HIV/AIDS

The growth rate of HIV/AIDS in India can be examined through three indicators, such as prevalence, incidence, and mortality rates, as well as trends over time. The HIV/AIDS epidemic in India started in the early 1980s, with the first case reported in 1986. By the mid-1990s, HIV had spread rapidly, especially among high-risk groups such as commercial sex workers, intravenous drug users, and men having sex with men. In the 1990s, the annual number of new infections was growing exponentially, with HIV spreading quickly from urban areas to rural regions. The mortality rate was initially low, as HIV progressed to AIDS after several years. However, by the end of 1990s, AIDS-related deaths increased significantly due to limited access to antiretroviral therapy (ART).

Table 1: Growth of Prevalence, Incidence and Deaths of HIV/AIDS in India

Years	Incidence rate	Growth rates	Prevalence rate	Growth rates	Deaths (in Lakhs)	Growth rates
2000	0.18		0.4		1.23	
2001	0.16	-11.78	0.41	2.47	1.44	15.76
2002	0.15	-3.23	0.45	4.65	1.61	5.58
2003	0.14	-2.30	0.43	-1.52	1.77	3.16
2004	0.14	0.00	0.41	-1.19	1.9	1.77
2005	0.13	-1.48	0.39	-1.00	1.96	0.62
2006	0.13	0.00	0.36	-1.33	2.01	0.42
2007	0.12	-1.14	0.34	-0.82	1.93	-0.58
2008	0.12	0.00	0.32	-0.76	1.86	-0.46
2009	0.11	-0.97	0.31	-0.35	1.72	-0.87
2010	0.1	-0.95	0.32	0.32	1.5	-1.37
2011	0.09	-0.96	0.31	-0.29	1.29	-1.37
2012	0.08	-0.98	0.3	-0.27	1.14	-1.03
2013	0.08	0.00	0.28	-0.53	0.98	-1.16
2014	0.07	-0.95	0.27	-0.26	0.82	-1.27
2015	0.06	-1.03	0.26	-0.25	0.77	-0.42
2016	0.06	0.00	0.25	-0.25	0.7	-0.60
2017	0.06	0.00	0.24	-0.24	0.61	-0.81
2018	0.06	0.00	0.23	-0.24	0.56	-0.48
2019	0.05	-0.96	0.22	-0.23	0.39	-1.90
2020	0.05	0.00	0.21	-0.23	0.28	-1.66
2021	0.05	0.00	0.21	0.00	0.23	-0.94

Table 1 shows the growth rates of prevalence, incidence and deaths. It is noticed that the growth in prevalence began to stabilize during 2000 to 2005. The National AIDS Control Program (NACP) launched in 1992, began gaining momentum in the early 2000s. New infection rates began to slow in response to prevention efforts targeting high-risk groups. Programs focusing on promoting condom use, safe injection practices, and public awareness contributed to reducing the incidence during this period. In deaths, the relative growth rate is applauding so the mortality continued to increase due to a lack of widespread ART, though advocacy for better treatment access started to take shape during this period.

The growth rate of HIV/AIDS prevalence started to decline gradually in the period of 2006 to 2012 as ART became more accessible and public health interventions were scaled up under NACP Phase III. The stabilization of the epidemic was seen as a result of increasing awareness and prevention programs. The annual number of new HIV infections showed a steady decline. In 2006, approximately 2.7 million people were living with HIV in India, but this number began to stabilize toward the end of the decade (NACO, Year). Meanwhile the introduction of free ART in 2004 helped to reduce AIDS-related deaths. By 2010, more people had access to treatment, which resulted in a decline in mortality rates. Further decline in relative growth rates in 2011 to 2015 is observed. According to NACO, there was a 13% reduction in HIV prevalence between 2010 and 2015 and the new infections continued to decrease significantly. Between 2007 and 2015, the incidence rate of HIV dropped by around 50% due to the extensive prevention campaigns, testing, and treatment. Mortality from AIDS-related causes also showed a back down. In 2015, AIDS-related deaths reduced by 54% from the peak in the mid-2000s.

2016 to 2020 is considered as consolidating gains period because the relative growth rates of prevalence, incidence, and deaths deteriorated. By 2020, India had managed to reduce the overall HIV prevalence rate to below 0.25% of the adult population. The growth rate of prevalence was now stable, reflecting the success of ongoing programs. India achieved a steady decline in new infections, with a reduction of around 37% between 2010 and 2020. High-risk groups remained a focus of prevention efforts, though some regions still faced rising infections, particularly in the north-eastern states. The mortality rate continued to drop with the widespread availability of ART, with AIDS-related deaths decreasing by 66% compared to 2005 levels. In 2021, the prevalence of HIV remained stable at around 0.2-0.3%. However, a Post-Pandemic Era because the COVID-19 pandemic disrupted HIV services in some areas, leading to concerns about temporary setbacks in testing and treatment coverage. The incidence of new HIV infections showed a decline, but the rate of reduction slowed down in some areas due to pandemic-related service interruptions. AIDS-related deaths continued to decline, although some disruptions during the pandemic raised concerns about temporary increases in mortality among untreated populations.

Table 2: Overall Growth Trend Summary

Year Range	Prevalence Growth	Incidence Rate	Mortality Rate
2000-2005	Slow growth	Slowed incidence growth	Mortality rising
2006-2010	Stabilizing	Declining significantly	Mortality decreasing due to ART
2011-2015	Decline in growth rate	Further reduction	Continued decline
2016-2020	Stable Prevalence	New infections falling	Significant reduction
2021	Stable with challenges	Continued decline (slower)	Mortality declined further

India has witnessed a declining growth rate in terms of new HIV infections, prevalence, and mortality due to sustained government efforts, community-based interventions, and the scale-up of ART. However, disparities remain in some regions and populations, requiring ongoing focus and resources to sustain and improve these gains.

3.2 Growth Models of HIV/AIDS

HIV/AIDS incidence rate in India is observed from NACO report from 2000 to 2021. The data reveals that in 2000 incidence rate was 0.18 and it is declined to 0.05 in 2021, which shows that there is sharp decline for the span of 21 years that is the decline was 72% (see Table 3). Two growth curve models namely exponential growth model and Logarithmic growth curve model are applied to study the growth pattern of the incidence rate. The results shows that estimated value of exponential growth curve is very close to observed value (Fig. 1).

Table 3: Estimated values of Incidence rate of HIV/AIDS using growth models

Year	Incidence rate	Exponential Growth model	Logarithmic Growth model
2000	0.18	0.163595	0.202807
2001	0.16	0.157495	0.170319843
2002	0.15	0.151395	0.151316074
2003	0.14	0.145295	0.137832686
2004	0.14	0.139195	0.127374157
2005	0.13	0.133095	0.118828917
2006	0.13	0.126995	0.11160402
2007	0.12	0.120895	0.105345529
2008	0.12	0.114795	0.099825148
2009	0.11	0.108695	0.094887
2010	0.1	0.102595	0.090419901
2011	0.09	0.096495	0.08634176
2012	0.08	0.090395	0.082590233
2013	0.08	0.084295	0.079116862
2014	0.07	0.078195	0.075883231
2015	0.06	0.072095	0.072858371
2016	0.06	0.065995	0.070016952
2017	0.06	0.059895	0.067337991
2018	0.06	0.053795	0.064803911
2019	0.05	0.047695	0.062399843
2020	0.05	0.041595	0.060113094
2021	0.05	0.035495	0.057932744

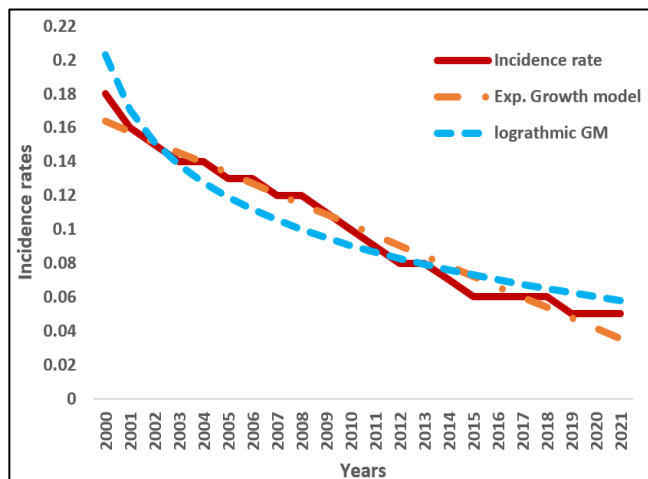


Fig 1: Estimated values of Incidence rate of HIV/AIDS using growth models

Table 4: Model Performance Metrics for incidence rate

Metric	Exponential	Logarithmic
MAPE	7.177574436	10.98710674
MALPE	0.07355658754	0.1075014031
MAE	0.005522727	0.009854696
RMSE	0.007083622	0.011510289
RAE	0.157792208	0.281562739
RRSE	0.179936183	0.292381109
R-SQUARED	0.967623365	0.91451329

The exponential growth model consistently outperformed the logarithmic growth model across various error metrics, indicating its superior predictive accuracy for incidence rates. The Mean Absolute Percentage Error (MAPE) for the exponential model was 7.17%, lower than the logarithmic model's 10.98%, demonstrating a smaller average deviation from actual values. Similarly, the Mean Absolute Logarithmic Percentage Error (MALPE) was 0.07 for the exponential model, compared to 0.10 for the logarithmic model, showcasing more consistent predictions across varying incidence levels. The Mean Absolute Error (MAE) further highlighted the exponential model's advantage, with a value of 0.005 new infection cases versus 0.009 for the logarithmic model, indicating closer alignment with actual infection counts. The Root Mean Square Error (RMSE) was also lower for the exponential model at 0.007 new infection cases compared to 0.011 for the logarithmic model, suggesting better handling of outliers and fewer large prediction errors. Furthermore, the Relative Absolute Error (RAE) for the exponential model was 0.157, reflecting a total absolute error that is only 15% of that of a naive model, whereas the logarithmic model's RAE was significantly higher at 0.281. The Relative Root Square Error (RRSE) followed a similar pattern, with the exponential model scoring 0.179 and the logarithmic model 0.292, underscoring the exponential model's superior fit to the data. Finally, the R-squared (R^2) value for the exponential model was an impressive 0.96, indicating it explained 96% of the variance in incidence rates, compared to 0.91 for the logarithmic model. Collectively, these metrics highlight the exponential growth model's ability to more accurately capture and predict trends in incidence rates.

Table 5: Estimated Values of Prevalence rate of HIV/AIDS using growth models

Year	Prevalence rate	Exponential Growth Model	Logarithmic Growth Model
2000	0.4	0.433595	0.495171
2001	0.41	0.422255	0.438345568
2002	0.45	0.410915	0.405104821
2003	0.43	0.399575	0.381520135
2004	0.41	0.388235	0.363226432
2005	0.39	0.376895	0.348279388
2006	0.36	0.365555	0.335641843
2007	0.34	0.354215	0.324694703
2008	0.32	0.342875	0.315038641
2009	0.31	0.331535	0.306401
2010	0.32	0.320195	0.298587303
2011	0.31	0.308855	0.291453956
2012	0.3	0.297515	0.284891913
2013	0.28	0.286175	0.278816411
2014	0.27	0.274835	0.273160253
2015	0.26	0.263495	0.267869271
2016	0.25	0.252155	0.262899157
2017	0.24	0.240815	0.258213209
2018	0.23	0.229475	0.253780683
2019	0.22	0.218135	0.249575568
2020	0.21	0.206795	0.245575664
2021	0.21	0.195455	0.241761871

The prevalence rate is estimated by two growth curves namely exponential and logarithmic growth curves. The analysis shows that there is 47. 5% declines from 2000 to 2021. The parameters of the models are estimated by the method of least squares. The analysis shows that the exponential curve shows good fit since the estimated values are nearer to observed values.

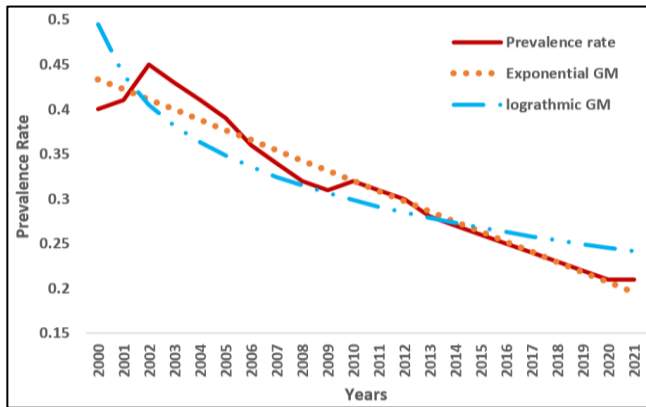


Fig 2: Estimated Values of Prevalence rate of HIV/AIDS using growth models

Table 6: Model Performance Metrics for prevalence rate

Metric	Exponential	Logarithmic
MAPE	3.316625	8.134957
MALPE	0.03322813	0.07983383
MAE	0.01163	0.026032
RMSE	0.01639	0.03326
RAE	0.186876	0.418304
RRSE	0.222153	0.450823
R-SQUARED	0.950648185	0.796759

Based on these metrics, the Exponential Growth Model outperforms the Logarithmic Growth Model in predicting prevalence rates. It achieves a significantly lower MAPE (3.31% vs. 8.13%) and MALPE (0.033 vs. 0.079), indicating greater accuracy and a better fit for datasets with outliers. The Exponential Model also shows smaller absolute deviations, with a lower MAE (0.011 vs. 0.026) and RMSE (0.0163 vs. 0.0332), reflecting more precise predictions and reduced sensitivity to large errors. Additionally, its RAE (0.186 vs. 0.418) and RRSE (0.222 vs. 0.450) highlight its superior

performance over a naive model. With an R^2 of 0.95, compared to 0.79 for the Logarithmic Model, the Exponential Growth Model explains more variance in prevalence rates, making it the preferred choice.

The deaths due to HIV / AIDS and their estimated value using two growth curves, Polynomial and logarithmic curve are presented in Table 7. The analysis of the data shows deaths due to HIV/AIDS is declined by 75.6% from 2000 to 2021. The polynomial curve shows good fit as its estimated value is collinear to observed number of deaths but logarithmic model shows very poor fit.

Table 7: Estimated Values of Deaths of HIV/AIDS using growth models

Year	Deaths (in Lakh)	Polynomial Growth Model	Logarithmic Growth Model
2000	1.23	1.2079	2.180183
2001	1.44	1.47142	1.877104395
2002	1.61	1.669	1.699814777
2003	1.77	1.80619	1.574025791
2004	1.9	1.8886	1.476456273
2005	1.96	1.92178	1.396736172
2006	2.01	1.91134	1.329333787
2007	1.93	1.86284	1.270947186
2008	1.86	1.78187	1.219446554
2009	1.72	1.674	1.173377668
2010	1.5	1.54482	1.131703292
2011	1.29	1.3999	1.093657567
2012	1.14	1.24483	1.058658893
2013	0.98	1.08519	1.026255183
2014	0.82	0.92655	0.99608805
2015	0.77	0.7745	0.967868581
2016	0.7	0.63462	0.941360465
2017	0.61	0.51249	0.916367949
2018	0.56	0.41368	0.892727056
2019	0.39	0.34378	0.870299063
2020	0.28	0.30837	0.848965564
2021	0.3	0.31302	0.828624687

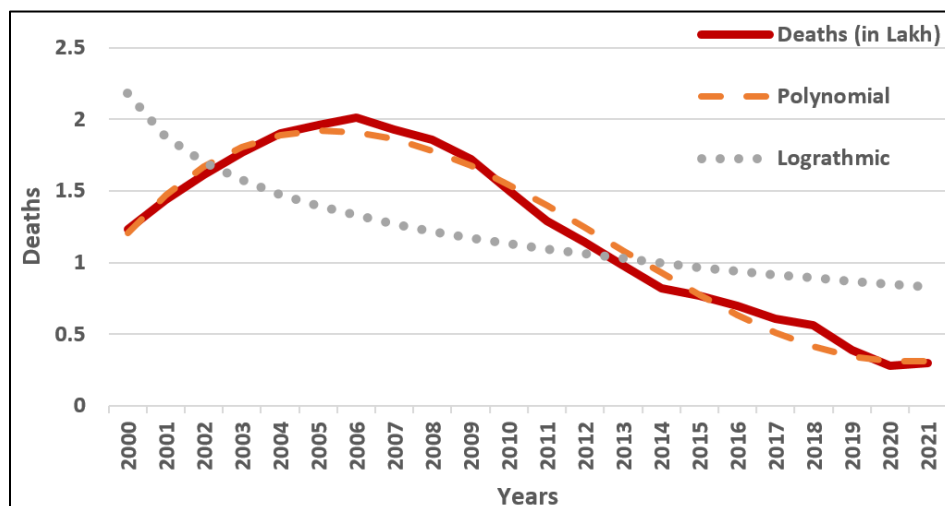


Fig 3: Estimated Values of Deaths of HIV/AIDS using growth models

Table 8: Model Performance Metrics for deaths due to HIV/AIDS

Metrics	Polynomial Growth Model	Logarithmic Growth Model
MAPE	6.831516171	47.954525
MALPE	0.07030738504	0.37834761
MAE	0.061858636	0.3959689
RMSE	0.07265699	0.4569455
RAE	0.121114802	0.7752789
RRSE	0.126068042	0.7928518
R-SQUARED	0.992075078	0.6094145

In predicting HIV/AIDS mortality rates, we employed both a polynomial growth model and a logarithmic growth model. We assessed the accuracy and fit of each model using key performance metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Logarithmic Percentage Error (MALPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Relative Absolute Error (RAE), Root Relative Squared Error (RRSE), and R-Squared (R^2). The results of each model's performance are summarized in the Table 8. The test for consistency and bias reveals that the polynomial model outperforms the logarithmic model in predicting mortality rates. With a much lower MAPE of 6.83 compared to 47.95 for the logarithmic model, the polynomial model demonstrates superior accuracy. Its smaller MALPE of 0.070 versus 0.378 further indicates more consistent performance, even when data deviates from a logarithmic pattern.

The polynomial model also achieved a lower MAE of 6.18% deaths compared to 39.59% for the logarithmic model, reflecting closer alignment with actual values. Its RMSE of 0.0726, significantly smaller than the logarithmic model's 0.4569, highlights its ability to handle outliers and large discrepancies effectively. In relative errors, the polynomial model's RAE of 0.1211 and RRSE of 0.126 are far superior to the logarithmic model's RAE of 0.775 and RRSE of 0.792, confirming its stronger fit. Additionally, the polynomial model achieved an R-squared (R^2) value of 0.99, explaining 99% of the variance in mortality rates, compared to just 60% for the logarithmic model. These findings emphasize the polynomial model's superior ability to capture mortality rate trends, making it the more reliable choice for analysis.

4. Conclusion

Analyzing HIV/AIDS using growth rates provides a comprehensive view of how the epidemic evolves over time. Prevalence, incidence, and mortality growth rates offer critical insights into the effectiveness of interventions and the status of the disease in different regions and populations. By closely monitoring these rates and adapting strategies accordingly, public health officials can make informed decisions to reduce the burden of HIV/AIDS and move towards achieving global health goals for HIV/AIDS eradication or control.

The comparative analysis of the exponential and logarithmic growth models for predicting HIV/AIDS incidence rates consistently shows that the exponential model outperforms the logarithmic model across all metrics. The exponential model's lower MAPE, MALPE, MAE, RMSE, RAE, and RRSE values, combined with its higher R^2 , demonstrate its superior predictive accuracy and reliability. This suggests that the exponential model is better suited for modeling HIV/AIDS incidence rates, offering more precise and consistent predictions. Similarly, when comparing the exponential and logarithmic growth models, the exponential model proves to be more effective in predicting HIV/AIDS prevalence rates. Its superior performance in terms of lower MAPE, MALPE, MAE, RMSE, RAE, and RRSE values, along with a higher R-squared, indicates that the exponential model is better at handling variance and outliers. This makes the exponential model a more reliable tool for public health officials, aiding in more accurate planning and intervention strategies for HIV/AIDS control. In the case of HIV/AIDS mortality, the polynomial growth model also proves to be more effective than the logarithmic model. The polynomial model consistently outperforms the logarithmic model across all statistical metrics, including MAPE, MALPE, MAE,

RMSE, RAE, RRSE, and R^2 . The polynomial model's ability to capture non-linear changes over time likely contributes to its superior performance, making it a more accurate representation of mortality trends and a valuable tool for public health analysis and strategy.

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