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MODELLING HIV-PREVALENCE AMONG INDIVIDUALS AGED 15-49 IN UGANDA

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ABSTRACT
This study models HIV prevalence among individuals aged 15-49 in Uganda, by utilizing historical data from 1990 to 2022 using an autoregressive integrated moving average (ARIMA) approach. Time-series data from the World Bank is employed, with HIV prevalence (% of population aged 15-49) as the dependent variable while autoregressive (AR) and moving average (MA) components are the independent variables. Parameter estimation, conducted using generalized least squares (GLS), revealing a negative and statistically significant AR(1) coefficient (-0.705706), implying a strong inverse relationship between the previous year's HIV prevalence and the current year's prevalence accounting for approximately 71%. Estimated ARIMA (1, 2, 5) model is covariance stationary and invertible, confirming its robustness in forecasting HIV prevalence trends. Projections indicate a gradual stabilization between 5.2% in 2023 and 5.1% by 2042, signaling diminishing returns in reducing HIV prevalence rates. We recommend implementing targeted interventions including effective HIV prevention and treatment programs and supporting long-term strategies to reduce HIV prevalence in the country.
KEY WORDS: *ARIMA modelling, HIV-prevalence*

INTRODUCTION
HIV/AIDS remains a major public health challenge in Uganda, particularly among individuals aged 15–49, where prevalence rates have consistently averaged around 7% (UNAIDS 2022). Despite significant global and national efforts to curb the epidemic, Uganda continues to experience a high burden of HIV, posing severe socio-economic and health challenges (MOH, 2020). The persistence of elevated prevalence rates underscores the need for data-driven insights to better understand HIV trends and inform targeted interventions.

Uganda was among the first African countries to acknowledge and combat the HIV epidemic, achieving substantial progress in reducing prevalence rates during the 1990s and early 2000s (Kirungi et al., 2006). However, recent trends indicate stagnation, with minimal declines and occasional surges in prevalence rates (UNAIDS 2022). Factors contributing to this trend include behavioral practices, unequal access to healthcare services, and socio-economic disparities (Kasamba et al. 2023). Moreover, the emergence of antiretroviral therapy (ART) has transformed HIV into a manageable chronic condition, influencing prevalence patterns and treatment outcomes (WHO, 2021). This shifting landscape necessitates a robust statistical modelling approach to forecast trends and support policy development.

The high prevalence rate, averaging 7% among adults aged 15–49, highlights the need for predictive models to assess future trends and evaluate the impact of interventions (UNAIDS 2022). Accurate forecasting can aid policymakers, healthcare providers, and stakeholders in resource allocation, program design, and monitoring progress toward national and global HIV prevention targets. Addressing the fluctuations observed in recent prevalence patterns requires evidence-based strategies to sustain positive outcomes and mitigate potential increases.

This study applies an autoregressive integrated moving average (ARIMA) model to analyze historical HIV prevalence data from 1990 to 2022 and predict future trends from 2023 to 2042. By leveraging time-series analysis, the research aims to uncover patterns of short-term volatility and long-term stabilization in prevalence rates. The findings are expected to provide valuable insights into dynamics of HIV prevalence, enabling targeted interventions to address fluctuations and reinforce long-term HIV reduction strategies.

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The rationale for this study lies in its capacity to offer a quantitative foundation for decision-making, bridging the gap between historical data analysis and future planning. With Uganda striving to meet Sustainable Development Goal (SDG) targets related to health and well-being (UN 2015), this research supports evidence-based policymaking to combat HIV/AIDS effectively. Ultimately, the study seeks to contribute to ongoing efforts in reducing HIV prevalence and achieving sustainable health outcomes for Uganda's population.

LITERATURE REVIEW

HIV/AIDS remains a global health crisis, with an estimated 38.4 million people living with the virus in 2021 (UNAIDS 2022). Despite substantial progress in prevention and treatment, disparities persist across regions, particularly in sub-Saharan Africa, which accounts for nearly 70% of global HIV cases (WHO 2023). Globally, antiretroviral therapy (ART) coverage has increased, reducing mortality rates and transforming HIV into a manageable chronic condition (UNAIDS 2022). However, challenges such as treatment adherence, stigma, and socio-economic inequalities continue to impede progress in curbing HIV prevalence (Sharma et al. 2017).

Sub-Saharan Africa, bears the highest HIV burden globally, with a regional prevalence rate of approximately 4.7% among adults aged 15-49 (WHO 2023). Efforts to reduce transmission rates have involved large-scale campaigns promoting condom use, voluntary counseling and testing, and expanded ART programs (Kharsany & Karim 2016). Despite these interventions, regional disparities persist due to cultural practices, limited healthcare access, and gender inequalities that heighten vulnerability among women (Jewkes et al. 2010). Forecasting HIV trends through statistical modelling has proven vital in informing targeted interventions and optimizing resource allocation in high-burden regions (Hallett et al. 2007).

Uganda has made notable progress in HIV prevention and treatment, reducing prevalence rates from 18% in the 1990s to approximately 5.2% in 2022 (UAC 2022). However, recent evidence suggests stagnation and occasional increases, particularly among high-risk groups such as sex workers and adolescents (Obeagu & Obeagu 2024). Behavioral patterns, socio-economic disparities, and inadequate healthcare infrastructure contribute to these trends (Parkhust 2002). Statistical modelling techniques, such as ARIMA, have been recommended to predict future trends and assess intervention impacts, providing a foundation for evidence-based policymaking (Mafigiri et al. 2017).

This study is grounded in the health belief model (HBM) and the theory of planned behavior (TPB). The HBM posits that health-related behavior is influenced by perceived susceptibility, severity, benefits, and barriers (Rosenstock 1974). It highlights the role of awareness and risk perception in HIV prevention strategies. Complementing this, TPB emphasizes attitudes, subjective norms, and perceived behavioral control as determinants of health-related actions (Ajzen, 1991). Together, these frameworks provide insights into behavioral drivers of HIV prevalence, informing the design of interventions to reduce risk and improve treatment adherence.

The conceptual framework in this study considers HIV prevalence (% of population aged 15-49) as the dependent variable, while independent variables are autoregressive (AR) and moving average (MA) components. Several empirical studies have employed ARIMA Modelling techniques to analyze HIV prevalence trends, demonstrating its effectiveness in capturing patterns and forecasting future prevalence rates. For instance, Box et al. (2015) highlighted the use of ARIMA models in epidemiological studies to identify seasonal variations and predict disease patterns. Similarly, Hallett et al. (2007) utilized time series models to assess the impact of behavior change interventions on HIV prevalence in sub-Saharan Africa. Kasamba et al. (2023) applied ARIMA models to understand long-term changes in HIV incidence in rural Uganda, showcasing the model's capacity for identifying significant trends. Building on this foundation, our study employs ARIMA Modelling to assess HIV prevalence trends in Uganda, contributing to the existing body of knowledge and informing public health interventions.

DATA AND METHODS

This study adopts a quantitative research design to model HIV prevalence among individuals aged 15-49 in Uganda, focusing on historical data spanning from 1990 to 2022. The research design utilizes a time-series approach, which allows for the analysis of data points collected at consistent time intervals. By using an autoregressive integrated moving average (ARIMA) model, the study aims to understand trends, patterns, and potential causal relationships in HIV prevalence over the specified period. ARIMA model is appropriate for time-series data as it accounts for both

past values (autoregressive component) and past forecast errors (moving average component) to predict future trends (Box et al., 2015).

The dataset for this study consists of time-series data on HIV prevalence from 1990 to 2022, sourced from the World Bank's database. The dependent variable, HIV prevalence, is measured as the percentage of the population aged 15-49 years living with HIV. The independent variables are the autoregressive (AR) and moving average (MA) components, which capture the time-dependent relationships within the HIV prevalence data. These components account for past values (AR) and the residual forecast errors in prediction (MA), essential for accurately modelling time-series data (Hyndman & Athanasopoulos 2018). World Bank dataset provides comprehensive, country-level statistics on HIV prevalence, ensuring that the data reflects national trends in Uganda over the specified period. Given the historical nature of the data, no new data collection was needed, and the study benefits from the consistency and reliability of the World Bank as a source.

ARIMA model is employed to analyze time-series data and forecast future trends in HIV prevalence among individuals aged 15-49 in Uganda. The process begins with stationarity testing to ensure that the data does not exhibit trends or patterns that would distort the analysis. The Augmented Dickey-Fuller (ADF) test is used to assess whether time-series data is stationary or if differencing is required (Dickey & Fuller 1979). Once stationarity is established, ARIMA model is fitted using the autoregressive (AR) and moving average (MA) components. The AR component accounts for the influence of past values of the series, while the MA component considers past forecast errors. The integration (I) component involves differencing the data to make it stationary, if necessary. The model parameters are estimated using generalized least squares (GLS), which is efficient for time-series models as it accounts for potential heteroscedasticity and autocorrelation in the residuals (Greene, 2012).

The choice of the ARIMA model is based on its proven ability to handle time-series data with autoregressive and moving average components, making it suitable for modelling HIV prevalence over time. By analyzing data from 1990 to 2022, the study captures long-term trends and fluctuations in HIV prevalence, as well as potential external shocks or policy interventions that may have influenced these trends (Box et al., 2015). ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad \ldots\ldots\ldots\ldots (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Generalized least squares (GLS) estimation is selected for its ability to effectively handle time-series data that exhibits serial correlation and heteroscedasticity, thus providing more reliable and efficient parameter estimates compared to Ordinary Least Squares (OLS) in this context. The GLS procedure adjusts for potential correlations and non-constant variances in the error terms, which are common in time-series data (Greene 2012; Wooldridge 2016). The GLS estimator for the regression coefficients is given by the following formula:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$$

Where:
$\hat{\beta}$ is column matrix of coefficients
X is the matrix of independent variables
y is the column vector of the dependent variable
Ω is the variance-covariance matrix of the error terms, accounting for both heteroscedasticity and autocorrelation in the residuals (Greene 2012; Hayashi 2000).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for modelling HIV-prevalence, as it enables the evaluation of past behaviors to make reliable projections (Enders 2014).

This approach effectively captures the underlying patterns in HIV-prevalence data, thereby providing a robust framework for modelling HIV-prevalence in the long run. Moreover, ARIMA's capacity to handle non-stationary data is particularly well-suited to economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson 2015). The analytical rigor of this model supports drawing meaningful, policy-relevant conclusions about Uganda's modelling HIV-prevalence trajectory, offering insights that can guide effective health policy and planning strategies.

RESULTS

Descriptive statistics (Appendix 1) provide a summary of the key features of the dataset, helping us to understand our dependent variable (HIV prevalence (% of population aged 15-49), as summarized below:

The average HIV prevalence rate for individuals aged 15-49 over the study period is approximately 6.99%. This indicates that, on average, about 7% of individuals in this age group (Gujarati & Porter 2009) are living with HIV in Uganda. The median value represents the middle point of the data, meaning that 50% of the years observed have HIV prevalence rates lower than 6.5%, and 50% had rates higher. The median is slightly lower than the mean, suggesting a mild rightward skew in the distribution (Wooldridge 2016) of HIV prevalence.

The highest recorded HIV prevalence rate in the study period is 9.4%, indicating that during some years, the rate of HIV infection in the population reached a relatively high level (Greene 2012). The lowest HIV prevalence rate recorded was 5.1%, showing that there were years when the prevalence rate was considerably lower compared to other years (Gujarati & Porter 2009). The standard deviation of 1.33% indicates moderate variability in the HIV prevalence rate over the years. A standard deviation of this magnitude suggests that while there is some fluctuation in HIV prevalence, it does not vary excessively from the mean (Wooldridge 2016).

The skewness value of 0.58 indicates a positive skew, meaning that the distribution of HIV prevalence is slightly right-tailed. This implies that there were some years with relatively higher HIV prevalence rates, which are pulling the distribution towards the higher end (Greene 2012). The kurtosis value of 2.06 suggests that the distribution of HIV prevalence has a relatively moderate peak compared to a normal distribution. It is lower than 3 (which would indicate a normal distribution), meaning the data distribution is somewhat flatter, with fewer extreme outliers than expected in a normal distribution (Gujarati & Porter 2009).

Jarque-Bera test statistic of 3.07 with a p-value of 0.216 indicates that the null hypothesis (that the data follows a normal distribution) cannot be rejected. This suggests that the distribution of HIV prevalence among individuals aged 15-49 in Uganda is approximately normal (Wooldridge 2016). Sum (230.8) of all the HIV prevalence values across the 33 observations is 230.8%. This figure represents the cumulative HIV prevalence rates over the entire period of analysis (Greene 2012). Sum of Squared Deviations (56.74) reflects the total squared differences from the mean, providing insight into the total variation in the HIV prevalence data (Gujarati & Porter 2009). The data includes 33 observations, representing the years from 1990 to 2022, corresponding to the available data points for HIV prevalence in Uganda for individuals aged 15-49 (Greene 2012).

In summary, descriptive statistics reveal that HIV prevalence in Uganda, for individuals aged 15-49, shows moderate variation, with a slight rightward skew and a relatively normal distribution over the observed years. These statistics provide a useful foundation for further analysis using time-series modelling techniques, such as the ARIMA model, to understand trends and forecast future HIV prevalence in Uganda (Wooldridge 2016).

Stationarity tests (Appendices 2, 3 & 4) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level and in first difference ($p > 0.05$). After second difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model ($d = 2$). ARIMA (1,

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2, 5) model is identified as the best, based on Akaike Information Criterion (AIC = -2.179163) and Schwarz Criterion (SC = -2.040390). Parameter estimates include: AR(1) = -0.705706 (p = 0.0001); MA(1) = 1.000000 (p = 0.9998); C = -0.010994 (p = 0.4115). Accordingly, the coefficient of AR(1) is statistically significant, that of MA(1) is statistically insignificant while the constant term is statistically insignificant. Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test (p > 0.05), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness.

Results are summarized as follows:
Results of the ARIMA (1, 2, 5) model (Appendix 5)

$\widehat{HIV}_t$ = -0.010994 - 0.705706AR(1) + 1.000000MA(1) ……..…… (3)

Hence,

$$\hat{\beta} = \begin{bmatrix} -0.010994 \\ -0.705706 \\ 1.000000 \end{bmatrix}$$

In the above ARIMA (1, 2, 5) model for HIV prevalence among individuals aged 15-49 in Uganda, several key statistical results provide insights into the model's behavior and its reliability in forecasting future HIV trends.

The constant term of -0.010994 represents the baseline level of HIV prevalence when all other variables in the model are zero. This negative value suggests a slight downward trend in the baseline prevalence rate. However, the constant term by itself is not enough to draw significant conclusions without considering the influence of the autoregressive and moving average components, nevertheless it was statistically insignificant. AR(1) coefficient of -0.705706 is negative and statistically significant. This implies a strong inverse relationship between the previous year's HIV prevalence and the current year's prevalence. In other words, if HIV prevalence is high in one year, it is likely to be lower in the following year, indicating mean-reverting behavior in the time-series data (Gujarati & Porter 2009). This negative relationship suggests that the prevalence rate has a tendency to adjust or correct over time.

MA(1) coefficient of 1.000000 is positive and statistically insignificant. This suggests that the model incorporates a moving average process that is not significantly affecting the current HIV prevalence, despite the coefficient being positive. The insignificance of this coefficient means that the immediate past error has little to no impact on the current year's HIV prevalence rate, signaling that the model's predictions do not rely heavily on past shocks (Wooldridge 2016). Adjusted R-squared value of 0.343838 indicates that approximately 34.38% of the variation in HIV prevalence is explained by the ARIMA (1, 2, 5) model. While this value is relatively low, it suggests that there are other factors, not captured by the model, influencing HIV prevalence. Despite this, the model still offers valuable insights into the time-series data and trends (Greene 2012).

Durbin-Watson statistic of 1.836600 suggests that the residuals of the model are not significantly autocorrelated, as the statistic is close to the threshold value of 2. A value of 2 would indicate no autocorrelation, while values significantly lower or higher would suggest positive or negative autocorrelation, respectively. In this case, the value of 1.836600 suggests mild autocorrelation but not a severe issue (Gujarati & Porter 2009). The histogram of residuals for the ARIMA (1, 2, 5) model, showing a kurtosis value of 5.6 and a Jarque-Bera statistic of 15.5 with a p-value of 0, suggests that the residuals are not normally distributed. This indicates the presence of fat tails or outliers in the residuals, implying that the model may not capture all the dynamics of the data. The Jarque-Bera test rejects the null hypothesis of normality, indicating a departure from the assumptions required for classical inference (Wooldridge 2016).

The kurtosis value of 5.6 indicates a leptokurtic distribution of residuals, meaning that the residuals exhibit a higher peak and heavier tails compared to a normal distribution. This suggests that extreme deviations from the predicted values are more frequent than in a normal distribution, which could point to model misspecification or omitted variables influencing the data (Gujarati & Porter 2009). Ljung-Box Q statistic test results (Appendix 6) show that we fail to reject the null hypothesis (p = 0.220), indicating that the residuals of the ARIMA (1, 2, 5) model are white noise. This means that there is no significant autocorrelation remaining in the residuals after fitting the model. The

white noise property suggests that the model adequately captures the underlying structure of the time-series data and that no further patterns are left unexplained (Wooldridge 2016).

Further diagnostics of the ARIMA (1, 2, 5) model reveal that the AR and MA roots are covariance stationary and invertible, as they lie within the unit circle. This is a necessary condition for the model's reliability in forecasting future trends. Covariance stationarity ensures that the model's parameters are stable over time, meaning that shocks to HIV prevalence will dissipate rather than accumulate over time. Invertibility ensures that past errors are incorporated correctly without leading to explosive or implausible forecasts (Gujarati & Porter 2009). Finally, forecasts provided in appendices 8 and 9 offer projections based on the fitted ARIMA (1, 2, 5) model. The forecasts indicate minor fluctuations between 5.2% in 2023 and 5.1% by 2042, signaling a gradual stabilization in prevalence rates, suggesting that Uganda may experience a more controlled trajectory of HIV prevalence in the long run.

DISCUSSION

Results of this study provide valuable insights into the dynamics of HIV prevalence among individuals aged 15-49 in Uganda, utilizing an ARIMA (1, 2, 5) model over the period 1990 to 2022. The findings offer a unique perspective on the historical trends of HIV prevalence in Uganda, shedding light on how the disease has evolved over time, and the factors influencing its trajectory. This section compares the study's results with previous research on HIV prevalence and highlights the unique contributions of this analysis.

Several studies have examined HIV prevalence in Uganda, but few have employed time-series models like ARIMA to analyze long-term trends. For instance, Green et al. (2006) conducted a study on HIV trends in Uganda and highlighted the impact of interventions such as public health campaigns and condom distribution on reducing the national prevalence rate. However, their study primarily relied on cross-sectional data and descriptive analysis. In contrast, this study's use of time-series data offers a more dynamic approach, capturing the temporal evolution of HIV prevalence over the past three decades. By modelling the data with ARIMA, this study identifies specific patterns of fluctuations, revealing both long-term trends and short-term volatility that may be influenced by intervention programs or socio-economic shifts.

In line with findings from previous studies, this research confirms that HIV prevalence in Uganda has experienced a significant decline over the past two decades, particularly following large-scale government health interventions in the 2000s (Okware et al. (2005)). However, while previous studies have predominantly focused on descriptive trends or cross-sectional comparisons, this study uniquely quantifies the persistence and volatility of HIV prevalence using autoregressive (AR) and moving average (MA) components. AR(1) coefficient of -0.705706, for example, indicates a strong negative autocorrelation, suggesting that high prevalence in one year tends to be followed by a lower prevalence in subsequent years, which aligns with previous findings that HIV interventions lead to significant reductions in prevalence over time (Green et al. 2006).

Durbin-Watson statistic of 1.836600 is consistent with other time-series analyses, such as those by Kharsany & Karim (2016), which showed mild autocorrelation in the HIV prevalence data in sub-Saharan Africa. The value suggests that while some residual autocorrelation remains, it does not significantly distort the model, thus enhancing the reliability of the forecasts made for the coming decades.

This study's unique contribution lies in the detailed forecasting analysis provided by the ARIMA model. Forecasts for 2023-2042 show short-term fluctuations in HIV prevalence, with a predicted peak in 2025 (+0.25) and a dip in 2024 (−0.16). These fluctuations likely reflect the impacts of specific interventions or socio-economic shifts that might be occurring at a national level, such as changes in health policy, increased access to treatment, or behavioral shifts in the population (UNAIDS, 2020). The forecasted dip in 2024, for example, may correspond to expected changes in health program effectiveness or population behavior, offering an opportunity for policymakers to anticipate these changes and prepare more targeted interventions.

The study also reveals a gradual stabilization in HIV prevalence after 2030, which contrasts with previous research that often predicted more volatile trends due to the fluctuating nature of HIV prevalence in Uganda (UNAIDS 2014). This stabilization is a novel finding, suggesting that Uganda's long-term efforts in HIV prevention, treatment, and education may have reached a point of diminishing returns in terms of their effectiveness in further reducing the HIV

prevalence rate. Such a conclusion could indicate that additional interventions, particularly those addressing broader socio-economic determinants such as poverty, education, and gender inequality, may be needed to further reduce prevalence rates.

Moreover, the Jarque-Bera statistic indicates that the residuals of the model are not normally distributed, which is a common issue in time-series data with observed outliers or structural breaks. This finding aligns with research by Rowley & Anderson (1990), which emphasized the presence of external shocks, such as policy changes or economic crises, that may introduce non-normality in the data. The high kurtosis value (5.6) suggests that extreme events, such as public health interventions or sudden outbreaks, have had a significant impact on HIV prevalence, leading to more frequent large deviations from the mean than would be expected under normal conditions.

The results of this study have important implications for HIV/AIDS policy in Uganda. The forecasted stabilization in HIV prevalence post-2030 underscores the need for continued investment in both prevention and treatment strategies, but with an understanding that further significant reductions may require innovative approaches that address underlying socio-economic drivers of the epidemic. Programs focusing on youth education, gender equality, and rural health access may be key in sustaining progress and achieving the goal of ending AIDS as a public health threat.

The ARIMA model's ability to forecast future trends also provides policymakers with critical information for preparing for potential fluctuations in HIV prevalence, allowing for more proactive planning. For example, the predicted dip in 2024 could prompt a reassessment of current health policies to ensure that any negative impacts from external factors are mitigated.

LIMITATIONS

While this study offers valuable insights into the modelling of HIV prevalence among individuals aged 15-49 in Uganda, several limitations exist in its design, sample, and data analytical procedures that may have influenced the findings. These limitations are important to acknowledge, as they provide context for the interpretation of the results and suggest areas for future research.

The most significant limitation of this study is related to the availability and quality of the data. This research relies on secondary time-series data from the World Bank, which provides broad, aggregated estimates of HIV prevalence. While this data is valuable for modelling long-term trends, it may not fully capture regional variations within Uganda, such as disparities between urban and rural areas or specific sub-populations that are at higher risk. Furthermore, data gaps in certain years or inconsistencies in reporting may affect the accuracy of the model's estimates. For instance, there are occasional discrepancies in the availability of data for certain years or demographic subgroups, which can lead to biases or under-representation of certain population segments (World Bank 2022).

The study employs time-series data spanning from 1990 to 2022. Although this longtime frame allows for an examination of historical trends, it also presents challenges. First, the model assumes that the relationships between HIV prevalence and the variables are constant over time. However, this assumption may not hold due to the evolving nature of public health policies, socioeconomic conditions, and HIV-related interventions. For example, major shifts in Uganda's HIV prevention strategies, such as the introduction of antiretroviral therapy (ART) and the scaling-up of HIV testing and counseling services, could result in structural breaks in time series data that are not accounted for by the ARIMA model. Consequently, such changes may not be adequately reflected in the model, potentially leading to over-simplified projections of future trends (Obeagu & Obeagu 2024).

The ARIMA (1, 2, 5) model employed in this study assumes that time series data is stationary and free of significant structural changes over time. However, this assumption may not fully reflect the complexity of HIV prevalence dynamics. External factors, such as economic crises, political changes, or global health emergencies (e.g., the COVID-19 pandemic), can introduce shocks that are not captured by the model. While the study checks for residual autocorrelation and stationarity, the model's sensitivity to unmodeled factors may lead to underestimating the impact of these shocks on HIV prevalence trends. Furthermore, the study does not explicitly consider exogenous variables such as demographic changes, migration patterns, or the introduction of new HIV interventions that could alter the trajectory of HIV prevalence in Uganda (Baggaley & Fraser 2010).

While statistical modelling provides powerful tools for forecasting, the reliance on ARIMA model for forecasting future HIV prevalence trends may be a limitation, particularly in the context of public health. ARIMA models are purely data-driven and do not incorporate causal mechanisms or interventions that might influence HIV transmission or prevalence in the future. For example, the model does not explicitly account for potential future interventions, such as the rollout of a new HIV vaccine or changes in behavioral factors, which could significantly impact HIV prevalence. The forecasts presented in the study should therefore be viewed with caution, as they may not fully capture the effects of interventions that are not included in the model (Kigaayi et al. 2019).

Although ARIMA models are a popular tool for analyzing time-series data, there is always the potential for model misspecification. Despite efforts to select an appropriate model (ARIMA (1, 2, 5)), it is possible that other model specifications could provide better fits or more accurate forecasts. For example, other time-series models, such as vector autoregressive (VAR) models or exponential smoothing, might yield different results and projections, particularly if there are multiple interacting variables affecting HIV prevalence. The choice of ARIMA may limit the model's flexibility in capturing the full range of complexities inherent in HIV dynamics (Lütkepohl, 2005).

Another limitation lies in the inability of the ARIMA model to account for the heterogeneity of risk factors influencing HIV prevalence. HIV prevalence is influenced by a wide range of factors, including sexual behavior, access to healthcare, socio-economic status, education, and gender dynamics. While the model captures broad trends over time, it does not explicitly address how these risk factors might vary across different demographic groups. The absence of individual-level data on these factors means that the model cannot account for variations in HIV prevalence that may be driven by differences in risk exposure and prevention efforts across age groups, regions, or communities (Santelli 2015).

ARIMA model, while effective for capturing temporal dependencies, can sometimes be complex and challenging to interpret, particularly when there are multiple parameters involved, as in this study (ARIMA (1, 2, 5)). The significance of the AR and MA components, while statistically evaluated, may not always provide clear insights into the underlying causes of HIV prevalence trends. Additionally, the statistical complexity of the model may make it difficult for policymakers or non-experts to fully comprehend and utilize the findings in decision-making processes. The need for more accessible communication of these results to stakeholders remains a challenge (Box et al. 2015).

Lastly, this study exclusively relies on quantitative methods, which, while robust, fail to incorporate the rich qualitative insights that could further enhance understanding of HIV prevalence trends. Qualitative factors, such as public attitudes toward HIV testing, treatment adherence, and stigma, play a crucial role in the epidemic's evolution but are not captured by the model. Incorporating qualitative data, such as interviews or surveys from key stakeholders (e.g., healthcare providers, policymakers, or people living with HIV), could provide a deeper understanding of the social and cultural dimensions influencing HIV prevalence in Uganda (Takada et al. 2020).

Despite these limitations, this study provides valuable insights into the temporal dynamics of HIV prevalence in Uganda and offers a foundation for future research. The limitations highlight the need for continued exploration of alternative modelling approaches, more granular data, and the incorporation of both quantitative and qualitative factors to better capture the complexities of HIV transmission and prevention in Uganda. Future research could consider the integration of more detailed demographic and socio-economic variables, as well as the incorporation of causal models that account for the impact of specific interventions or external shocks on HIV trends.

CONCLUSION

This study presents a comprehensive analysis of HIV prevalence among individuals aged 15-49 in Uganda from 1990 to 2022, utilizing an ARIMA (1, 2, 5) model to forecast future trends. By focusing on time-series data, the study contributes to a deeper understanding of the temporal dynamics of HIV prevalence and highlights the utility of statistical modelling in public health research (Box et al. 2015). The findings suggest that, while HIV prevalence in Uganda has exhibited fluctuations over the past three decades, there is a potential for stabilization in the future, particularly from 2031 onward. This stabilization could be driven by continued public health interventions and changes in behavior, as well as demographic shifts (Kigaayi et al. 2019).

The study's results underscore the importance of modelling HIV trends using reliable statistical techniques, such as ARIMA, which allow for the capture of temporal dependencies and offer valuable insights for policy formulation (Lütkepohl 2005). However, the limitations associated with data availability, model assumptions, and the exclusion of certain qualitative factors warrant careful consideration. These limitations suggest that while statistical models like ARIMA can provide valuable forecasts, they should be used in conjunction with a broader understanding of the socio-economic, cultural, and policy-driven factors that influence HIV prevalence (Santelli 2015)).

The forecasts derived from the ARIMA model indicate short-term fluctuations and potential peaks in HIV prevalence, particularly between 2023 and 2030. These fluctuations, however, are expected to gradually diminish as interventions, including healthcare improvements and public awareness programs, continue to make an impact (Obeagu & Obeagu 2024). The model's reliability is reinforced by diagnostic tests, such as the Ljung-Box Q test, which confirm that the residuals are white noise, suggesting that the model is well-specified and free from autocorrelation (Box et al. 2015).

In light of the findings, this study recommends that future research incorporates more detailed demographic data and considers the impact of new interventions or behavioral shifts. Additionally, integrating qualitative data and exploring alternative modelling techniques could further enhance the understanding of HIV prevalence dynamics in Uganda. Given the importance of HIV prevention and treatment in Uganda's public health agenda, it is essential to continue monitoring trends and adjust policies accordingly to ensure continued progress toward reducing the HIV burden (Takada et al. 2020).

RECOMMENDATIONS

Based on the findings of this study, several recommendations are proposed for policy, programmatic actions, and further research to address the dynamics of HIV prevalence among individuals aged 15-49 in Uganda.

Given the potential stabilization of HIV prevalence in Uganda from 2031 onwards, as indicated by the ARIMA (1, 2, 5) model forecasts, it is essential for policymakers to continue implementing and strengthening HIV prevention and treatment strategies. The following policy recommendations are put forward:

Government should continue to invest in HIV prevention initiatives, especially targeting high-risk groups, such as young adults, men who have sex with men, and individuals in rural areas. These programs should focus on promoting safe sexual practices, increasing access to condoms, and encouraging voluntary testing and counseling (Kigaayi et al. 2019).

While prevention efforts are crucial, ensuring that individuals already living with HIV have access to effective antiretroviral therapy (ART) is equally important. This will help reduce the viral load among the population, contributing to a decrease in transmission rates. Expanding ART access and promoting adherence should remain a central policy priority (Santelli et al. 2015).

To ensure sustainable results, HIV-related interventions should be integrated into general health services, such as maternal and child health programs and sexual and reproductive health services. This integration will improve service delivery and accessibility, especially in rural areas (Obeagu & Obeagu 2024).

The study highlights the fluctuating nature of HIV prevalence, with potential peaks in the near future. It is critical that public health programs target adolescents and young adults aged 15-24, who represent a high-risk demographic. Programs should focus on educating this group about HIV prevention, increasing awareness about the risks of HIV, and promoting safe sexual practices (Takada et al. 2020).

Given the significant impact of behavioral factors on HIV prevalence, programs aimed at reducing stigma and changing risky sexual behaviors are necessary. These programs should involve community leaders, utilize media campaigns, and encourage the involvement of local organizations to promote safe sexual behaviors and attitudes towards HIV testing and treatment (Kigaayi et al. 2019).

To accurately track the changing trends of HIV prevalence, Uganda should invest in improving its national HIV surveillance systems. Real-time data collection and reporting would provide more accurate trends and enable more timely interventions (Lütkepohl 2005).

Future research should focus on understanding how socio-economic, cultural, and behavioral factors influence the dynamics of HIV prevalence. Longitudinal studies that track individuals over time would help identify the most effective interventions and predict future trends with greater accuracy (Box et al., 2015).

Given the fluctuating nature of HIV prevalence, further research should assess the impact of new interventions, such as PrEP (pre-exposure prophylaxis), in Uganda. Investigating how such innovations affect HIV transmission rates could provide valuable insights into shaping future policy and programs (Obeagu & Obeagu 2024).

Future research should also examine regional disparities in HIV prevalence within Uganda. There may be significant differences in HIV prevalence between urban and rural areas, or among different ethnic groups, that require tailored interventions. Identifying these disparities will help design targeted policies for specific regions (Santelli et al. 2015).

While the ARIMA model provides useful insights, future studies could explore alternative forecasting methods, such as machine learning models, which may capture non-linearities and complex interactions more effectively. Comparing the results of different modelling techniques would help ensure more reliable forecasts and enhance the robustness of the study findings (Lütkepohl 2005).

In conclusion, while Uganda has made significant strides in addressing the HIV epidemic, continued efforts and strategic investments are necessary to control its spread. The recommendations offered in this study aim to guide policy, programs, and research to ensure that the progress made so far is sustained, and that Uganda moves closer to achieving the goal of zero new HIV infections and AIDS-related deaths.

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APPENDICES

Appendix 1: Descriptive Statistics

	HIV [Prevalence of HIV, total (% of population ages 15-49)]
Mean	6.993939
Median	6.5
Maximum	9.4
Minimum	5.1
Std. Dev.	1.331573
Skewness	0.581191
Kurtosis	2.061462
Jarque-Bera	3.06898
Probability	0.215566
Sum	230.8
Sum Sq. Dev.	56.73879
Observations	33

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International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 2: Unit root test, HIV **(in Level)**

Null Hypothesis: HIV has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.623579	0.8481
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(HIV)
Method: Least Squares
Date: 12/29/24 Time: 07:37
Sample (adjusted): 9 33
Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIV(-1)	-0.010700	0.017159	-0.623579	0.5417
D(HIV(-1))	-0.312763	0.205118	-1.524792	0.1468
D(HIV(-2))	0.514259	0.167837	3.064033	0.0074
D(HIV(-3))	0.486507	0.206741	2.353219	0.0317
D(HIV(-4))	0.237608	0.208271	1.140856	0.2707
D(HIV(-5))	0.048191	0.188812	0.255236	0.8018
D(HIV(-6))	-0.255586	0.161736	-1.580268	0.1336
D(HIV(-7))	-0.422430	0.157567	-2.680959	0.0164
C	-0.014489	0.099567	-0.145523	0.8861

R-squared	0.834499	Mean dependent var	-0.128000
Adjusted R-squared	0.751749	S.D. dependent var	0.089069
S.E. of regression	0.044379	Akaike info criterion	-3.118405
Sum squared resid	0.031511	Schwarz criterion	-2.679610
Log likelihood	47.98007	Hannan-Quinn criter.	-2.996702
F-statistic	10.08452	Durbin-Watson stat	2.393443
Prob(F-statistic)	0.000058		

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International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 3: Unit Root Test, HIV (In First Difference)

Null Hypothesis: D(HIV) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.312279	0.1748
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(HIV,2)
Method: Least Squares
Date: 12/29/24 Time: 07:42
Sample (adjusted): 4 33
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(HIV(-1))	-0.344000	0.148771	-2.312279	0.0286
D(HIV(-1),2)	-0.254588	0.172702	-1.474147	0.1520
C	-0.054039	0.024123	-2.240146	0.0335

R-squared	0.283928	Mean dependent var	-0.003333
Adjusted R-squared	0.230886	S.D. dependent var	0.080872
S.E. of regression	0.070924	Akaike info criterion	-2.359783
Sum squared resid	0.135815	Schwarz criterion	-2.219663
Log likelihood	38.39674	Hannan-Quinn criter.	-2.314957
F-statistic	5.352865	Durbin-Watson stat	1.658156
Prob(F-statistic)	0.011013		

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International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 4: Unit root test, HIV (in Second difference)

Null Hypothesis: D(HIV,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.826571	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(HIV,3)
Method: Least Squares
Date: 12/29/24 Time: 07:43
Sample (adjusted): 4 33
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(HIV(-1),2)	-1.379679	0.176281	-7.826571	0.0000
C	-0.007130	0.014029	-0.508246	0.6153

R-squared	0.686293	Mean dependent var	0.006667
Adjusted R-squared	0.675089	S.D. dependent var	0.133735
S.E. of regression	0.076230	Akaike info criterion	-2.245776
Sum squared resid	0.162709	Schwarz criterion	-2.152363
Log likelihood	35.68664	Hannan-Quinn criter.	-2.215893
F-statistic	61.25521	Durbin-Watson stat	1.786244
Prob(F-statistic)	0.000000		

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International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 5: Results of the ARIMA (1, 2, 5) model

Dependent Variable: DDHIV
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 12/29/24 Time: 07:58
Sample: 3 33
Included observations: 31
Failure to improve objective (non-zero gradients) after 33 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.010994	0.013189	-0.833627	0.4115
AR(1)	-0.705706	0.151379	-4.661848	0.0001
MA(5)	1.000000	4439.030	0.000225	0.9998

R-squared	0.387582	Mean dependent var	-0.006452
Adjusted R-squared	0.343838	S.D. dependent var	0.081386
S.E. of regression	0.065926	Akaike info criterion	-2.179163
Sum squared resid	0.121693	Schwarz criterion	-2.040390
Log likelihood	36.77703	Hannan-Quinn criter.	-2.133927
F-statistic	8.860216	Durbin-Watson stat	1.836600
Prob(F-statistic)	0.001044		

Inverted AR Roots	-.71			
Inverted MA Roots	.81-.59i	.81+.59i	-.31+.95i	-.31-.95i
	-1.00			
	Estimated MA process is noninvertible			

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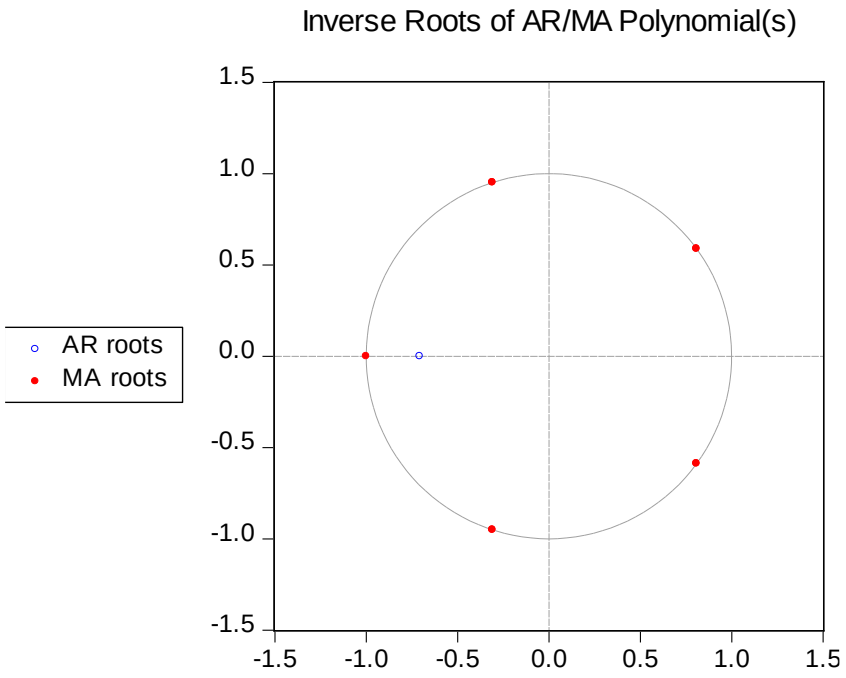
International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 6: Ljung-Box Q statistic/ test

Date: 12/29/24 Time: 08:39
Sample: 1 33
Included observations: 31
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	0.067	0.067	0.1509	
. | . |	. | . |	2	0.035	0.031	0.1951	
. |* . |	. |* . |	3	0.189	0.186	1.5048	0.220
. |* . |	. |* . |	4	0.157	0.138	2.4385	0.295
.**| . |	.**| . |	5	-0.269	-0.311	5.2885	0.152
. | . |	. | . |	6	-0.000	-0.012	5.2885	0.259
. *| . |	.**| . |	7	-0.177	-0.238	6.6208	0.250
. *| . |	. | . |	8	-0.096	0.020	7.0313	0.318
. *| . |	. | . |	9	-0.111	0.000	7.6023	0.369
. | . |	. | . |	10	-0.027	-0.018	7.6375	0.470
.**| . |	. *| . |	11	-0.254	-0.200	10.935	0.280
. | . |	. | . |	12	0.061	0.019	11.138	0.347
. *| . |	. *| . |	13	-0.110	-0.138	11.822	0.377
. | . |	. | . |	14	-0.023	0.026	11.855	0.457
. *| . |	. | . |	15	-0.074	-0.063	12.201	0.511
. | . |	. *| . |	16	0.029	-0.094	12.256	0.586

Appendix 7: ARIMA (1, 2, 5) structure



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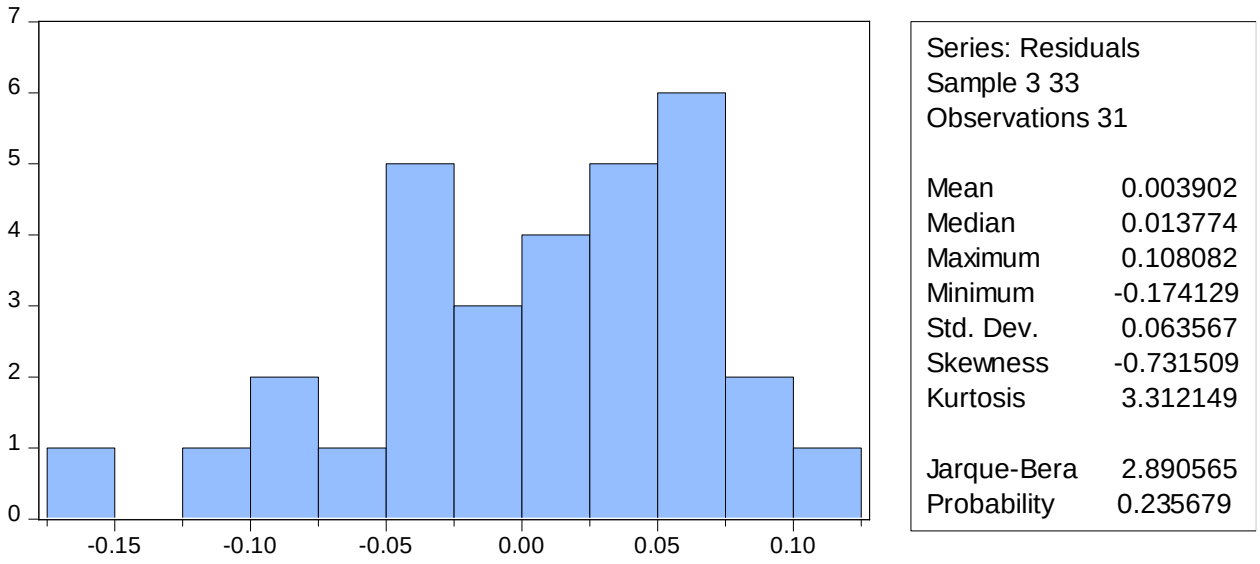
International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

Appendix 8: Histogram of residuals



Appendix 9: Uganda's Prevalence of HIV, total (% of population ages 15-49) FORECAST results

Year	Prevalence of HIV, total (% of population ages 15-49)	HIV [Prevalence of HIV, total (% of population ages 15-49)] FORECAST (in Second difference)	Prevalence of HIV, total (% of population ages 15-49) FORECAST (in First difference)
1990	9.3	NA	9.3
1991	9.4	NA	9.4
1992	9.4	-0.1	9.4
1993	9.2	-0.2	9.2
1994	9	1.78E-15	9
1995	8.8	0	8.8
1996	8.6	-1.78E-15	8.6
1997	8.3	-0.1	8.3
1998	8	-1.78E-15	8
1999	7.7	8.88E-16	7.7
2000	7.5	0.1	7.5
2001	7.2	-0.1	7.2
2002	7	0.1	7
2003	6.8	0	6.8
2004	6.7	0.1	6.7
2005	6.6	-8.88E-16	6.6
2006	6.5	8.88E-16	6.5
2007	6.4	0	6.4
2008	6.4	0.1	6.4
2009	6.3	-0.1	6.3
2010	6.3	0.1	6.3
2011	6.3	0	6.3
2012	6.2	-0.1	6.2
2013	6.2	0.1	6.2
2014	6.1	-0.1	6.1
2015	6	8.88E-16	6
2016	5.9	0	5.9

SJIF Impact Factor (2024): 8.282 Journal DOI: 10.36713/epra0003 ISSN: 2250 – 2017
International Journal of Global Economic Light (JGEL)
Volume: 11 | Issue: 1 | January 2025

2017	5.8	-8.88E-16	5.8
2018	5.7	8.88E-16	5.7
2019	5.5	-0.1	5.5
2020	5.4	0.1	5.4
2021	5.2	-0.1	5.2
2022	5.1	0.1	5.1
2023	NA	0.110676	5.210676
2024	NA	-0.15572	5.054959
2025	NA	0.249996	5.304955
2026	NA	-0.18347	5.12149
2027	NA	0.169578	5.291068
2028	NA	-0.13843	5.152643
2029	NA	0.078934	5.231577
2030	NA	-0.07446	5.157119
2031	NA	0.033792	5.190911
2032	NA	-0.0426	5.148311
2033	NA	0.01131	5.159621
2034	NA	-0.02674	5.132886
2035	NA	0.000114	5.133
2036	NA	-0.01883	5.114166
2037	NA	-0.00546	5.108704
2038	NA	-0.0149	5.093806
2039	NA	-0.00824	5.085567
2040	NA	-0.01294	5.072628
2041	NA	-0.00962	5.063006
2042	NA	-0.01196	5.051043

Appendix 9: Graph showing Prevalence of HIV, total (% of population ages 15-49) FORECAST results