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Forecasting HIV/AIDS Mortality in Adamawa State Using the Lee-Carter Model: Implications for Achievi4ng SDG-3

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Globally, HIV/AIDS remains a significant health concern, with profound impacts in developing nations, including Nigeria. This study aim to project mortality among HIV patients in Adamawa State using the Lee-Carter model to assess progress towards the third Sustainable Development Goal (SDG-3) - terminating AIDS by 2030. Mortality data for 2011-2020 on HIV patients aged 15-59 years receiving antiretroviral therapy (ART) was obtained from Adamawa State AIDS control database. The Lee-Carter model, using the Singular Value decomposition (SVD) for parameter estimation was fitted to estimate age-specific parameters. The time series component was forecast using ARIMA(0,1,0). Mortality data from 2011 to 2020 revealed a substantial 29.6% decrease in mortality, a testament to government and NGO interventions. The study delineates varied age group responses to improvements in mortality rates, pinpointing ages 55-59 as the most affected, while ages 15-19 exhibit the lowest mortality rates. Furthermore, individuals aged 20-24 show heightened responsiveness to general mortality improvements compared to other age cohorts. This work substantiates that Adamawa State has achieved substantial progress toward the SDG-3 target of a 90% decline in HIV/AIDS patient mortality rate, setting a promising trajectory towards an AIDS-free society by 2030. However targeted strategies are still needed for older patients.

Keywords: Mortality, HIV/AIDS, Lee-Carter Model, Projection, Nigeria.

1. INTRODUCTION

HIV/AIDS has remained a major public health concern for decades, affecting both the economic growth of sub-Saharan Africa and broader sustainable development efforts [1, 2]. Nigeria ranks among the top three countries globally with People Living with HIV (PLHIV) [3]. Although notable progress has been made in reducing HIV prevalence [4], in line with the goal of SDG-3 to ensure healthy lives and promote well-being for all, achieving the target of ending the epidemics of tuberculosis, AIDS, malaria and related conditions by 2030 requires a 90 percent decline in new infections and HIV/AIDS-related deaths between 2010 and 2030 [5]. As the year 2025 approaches, it remains critical to ask whether Nigeria, and particularly Adamawa State in the northeast, is on track to meet these expectations and how close current outcomes are to the SDG-3 milestones.

The modeling of future mortality remains a central challenge in actuarial science, and the Lee Carter (LC) model has become a widely accepted benchmark for mortality forecasting [6, 7]. The model's parsimonious structure and its strong performance in capturing general mortality trends have strengthened its use in settings where the availability of long-term data is limited or where mortality is undergoing rapid change [8, 9]. Although the LC model has been examined in various international contexts [10-16], its relevance for Nigeria is particularly important because the country continues to experience dynamic shifts in mortality patterns due to ongoing public health interventions, variations in access to care and differences in disease burden across regions. A forecasting approach that can capture these changes is therefore valuable for evaluating future health trajectories and planning resource allocation.

Despite the extensive use of the LC model to study general mortality, cause-specific mortality and mortality across demographic groups [17], there is limited evidence of its application to HIV/AIDS mortality in Nigeria. This represents a significant gap because reliable projections of HIV/AIDS mortality are essential for assessing the effectiveness of antiretroviral therapy (ART), monitoring the pace of progress toward SDG-3, and identifying areas where additional public health interventions may be required. The absence of such studies limits the evidence base needed for targeted planning, especially in regions with varying levels of disease burden such as Adamawa State.

To address this gap, the present study applies the Lee Carter model to project HIV/AIDS mortality in Adamawa State and evaluates how the projected trends align with SDG-3 targets as 2030 approaches. By estimating future mortality levels and assessing patterns that reflect the effectiveness of ART coverage, the study provides insight into the likely trajectory of HIV/AIDS mortality in the state and contributes to evidence-based decision-making for improved health outcomes.

2. METHODOLOGY

The selection of the Lee-Carter model for this analysis is supported by its established robustness and extensive application in demographic and actuarial literature for mortality forecasting over the past decades, making it a well-validated methodological choice [18]. For parameter estimation, we employed a straightforward and appropriate two-stage procedure. At the first stage, Singular Value Decomposition (SVD) was applied to the matrix of logged central mortality rates to obtain estimates of the age-specific parameters α_x and the general time trend (k_t). Subsequently, to generate future mortality trajectories, the time-series k_t parameter was extrapolated using a suitably identified ARIMA model.

2.1. ARIMA Model Specification

The ARIMA model specification was determined through a comprehensive analysis of the k_t series. While model selection was guided by the Akaike Information Criterion (AIC), the primary justification for the final ARIMA structure was based on a diagnostic examination of the series' autocorrelation (ACF) and partial autocorrelation (PACF) functions, which informed the appropriate orders of integration and autoregressive/moving-average components to ensure a stationary and well-fitting forecast model.

2.2. Study Data Description

This study utilizes ART-patient mortality data from Adamawa State for the period 2011–2020. This timeframe was selected as it corresponds with the consistent and scaled-up provision of Antiretroviral Therapy (ART) under Nigeria's national treatment guidelines, providing a coherent era for analysis. The data is considered reliable for this purpose as it originates from the state's health management information system (HMIS), which aggregates reports from designated treatment facilities. To ensure analytical integrity, the data underwent standard preprocessing to address potential issues such as missing entries or inconsistencies prior to model fitting.

2.3. Model Diagnostics and Validation

To validate the model's adequacy, a suite of diagnostic plots was generated. The goodness-of-fit was assessed by comparing observed mortality rates against those fitted by the model. Furthermore, an analysis of the residuals was conducted to check for randomness, homoscedasticity, and the absence of systematic patterns. Supplementary diagnostics, including Q-Q plots of residuals and the autocorrelation function of the residual series, were examined to verify that the model sufficiently captured the underlying data structure without significant bias or unexplained temporal correlation.

2.4. Source of data for the study

The data set used in this paper comprised of HIV/AIDS records of patients on ART for the period of ten years (2011-2020), the sample of interest is the number of deaths within each age group 15 - 59 for each year, obtained from Adamawa State Agency for the Control of AIDS database. All statistical data analyses and computations was carried out using *R Statistical Software* (R Foundation for Statistical Computing), Version 4.1.0.

2.5. Model Specification

The LC model is the model adopted for the purpose of this study and is explained as follows:

The LC model is a simple model comprises of two independent linear variables x which represent (age) and t which represent (time) or period, defined as

$$\ln m_{x,t} = \alpha_x + \beta_x k_t + \varepsilon_{x,t} \quad (1)$$

Where,

$m_{x,t} = \frac{d_{x,t}}{e_{x,t}}$, represent the matrix of mortality rate on a specific age group at age, x , ($x = x_1, \dots, x_n$) over a period (t) ($t = t_1, t_1 + 1, \dots, T - 1$), traditionally it is defined as the ratio of total death at age x in year t to the number of persons at risk at age x in year t .

α_x ; captures the average (overtime) of the logarithm the rate describing the general mean of the age profile.

β_x ; captures the sensitivity rate to the changes in general level of mortality at age x (it represents the rate at which an individual at age x will respond to changes attributed to general mortality fluctuations).

k_t ; represent the time index of the general level of mortality of the cohort under study.

$\varepsilon_{x,t}$; denotes the residual or a set of random error (white noise) from factors not captured by the model.

$$\varepsilon_{x,t} \sim N(0, \sigma^2), E(\varepsilon_{x,t}) = 0, var(\varepsilon_{x,t}) = \sigma^2 \quad (2)$$

The above parameters can be interpreted using sets of constraint as follows

$$\alpha_x = \frac{1}{T} \sum_t \ln m_{x,t} \quad (3)$$

$$k_t = \sum_x (\ln m_{x,t} - \alpha_x) \quad (4)$$

The equation $\hat{\alpha}_x = \frac{1}{T} \sum_{t=t_1}^T \ln(m_{x,t})$ represents the mortality evolution over time.

ARIMA Model:

To forecast the mortality index, the ARIMA model come in handy. After the estimation of the model parameters of the LC model, the kappa estimates are then fitted to the univariate model of ARIMA (0, 1, 0). After trying various techniques to forecast the time series component of the model, it turns out that the random walk with drift is the best model to forecast the kappa parameters. The model is given by

$$k_t = k_{t-1} + \theta + \varepsilon_t \quad (5)$$

Where;

θ : is the drift parameter.

ε_t : is the error term with mean zero and a variance $\varepsilon_t \sim N(0, \sigma^2)$. The drift parameter $\hat{\theta} = \frac{k_T - k_1}{T-1}$.

It is obvious that the drift parameter $\hat{\theta}$ depends only on the first and last of k_t estimates of the model. To forecast like two periods ahead, one need just to substitute for the definition of $\hat{k}_{t-1}$ which is denoted by $m_{x,t+1} e^{\hat{\alpha}_x + \hat{\beta}_x \hat{k}_t}$ moved back in time one period that is;

$$\begin{aligned} \hat{k}_t &= \widehat{k_{t-1}} + \hat{\theta} + \varepsilon_t \\ &= (\widehat{k_{t-2}} + \hat{\theta} + \varepsilon_{t-1}) + \hat{\theta} + \varepsilon_t \\ &= \widehat{k_{t-2}} + 2\hat{\theta} + (\varepsilon_{t-1} + \varepsilon_t) \end{aligned} \quad (6)$$

Now to forecast kappa $\hat{k}_t$ at any time period say $T + (\Delta t)$ using the data available for a period say T , we iterate the procedure for (Δt) times and obtain as follows:

$$\hat{k}_{T+(\Delta t)} = \widehat{k_T} + (\Delta t)\hat{\theta} + \sum_n^{(\Delta t)} \varepsilon_{T+n-1} \quad (7)$$

$$= \widehat{k_T} + (\Delta t)\hat{\theta} + \sqrt{(\Delta t)\varepsilon_t} \quad (8)$$

$$t=1, 2, \dots, T$$

3. RESULTS AND DISCUSSION

3.1. Mortality Patterns and Age-Specific Trends

The estimation of the α_x and β_x parameters of the LC model shows that mortality patterns vary significantly across different age groups. Since α_x is the first parameter in the LC model, it is obtained as the mean of the age-specific death rate across the years (time). And Figure 1 shows a line graph of α_x parameter of the Lee-Carter model.

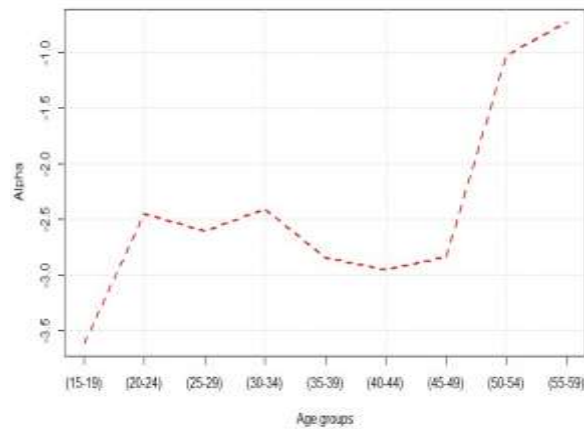


Figure 1: Graph of Estimated Alpha α_x

The α_x parameter, which represents the general level of mortality, is lower for younger age groups (15-19) and increases as individuals get older, particularly for those aged 50-59. This suggests that younger populations, particularly those in the age group of 15-19, experience the lowest mortality rates, potentially due to fewer HIV/AIDS-related deaths at this stage of life. This finding aligns with the general trend observed in HIV/AIDS research, where younger populations tend to have lower HIV-related mortality rates, as highlighted in previous studies [19, 20]. Conversely, the older age groups (50-59) exhibit higher mortality rates, indicating a more severe impact of HIV/AIDS in older populations. This observation is consistent with existing literature, which suggests that older HIV-positive individuals often experience more complications and higher mortality due to comorbidities and a slower immune response to treatment [21]. These findings are critical, as they emphasize the need for targeted healthcare interventions for older populations to reduce mortality rates and improve quality of life.

3.2. Responsiveness to Mortality Fluctuations

The estimation of the β_x parameter represents the rate at which individual at the age will respond to the changes attributed to general mortality fluctuations. It shows that individuals aged 20-24 are most sensitive to changes in the overall mortality rate (Figure 2). This finding indicates that individuals in this age group are more likely to experience improvements in survival as general mortality rates decrease. Previous research has shown similar trends, where younger adults (20-24) tend to benefit more from antiretroviral therapies (ART) and other medical interventions compared to older age groups, due to better adherence and immune recovery [22].

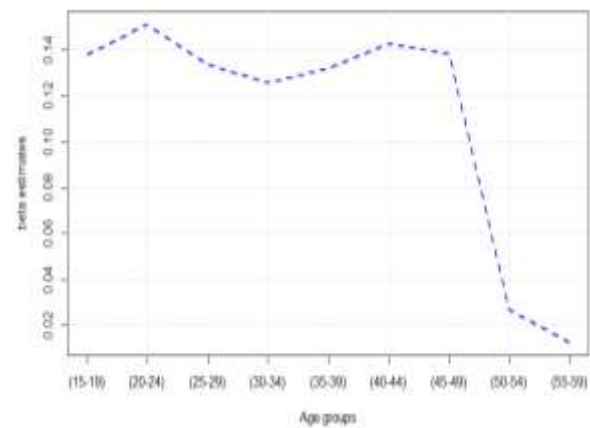


Figure 2: Graph of estimated Beta β_x

However, the β_x parameter also suggests that older individuals (50-59) are less responsive to changes in mortality, indicating that improvements in general mortality rates have a limited impact on this age group. This underscores the challenge of reducing mortality in older HIV-positive populations, as they often face multiple health challenges beyond HIV infection itself, such as cardiovascular diseases and diabetes [23].

3.2.1. Estimation of the κ_t Parameter of LC Model

Figure 3 shows the estimate of the time series component of the LC model for the estimated κ_t parameter.

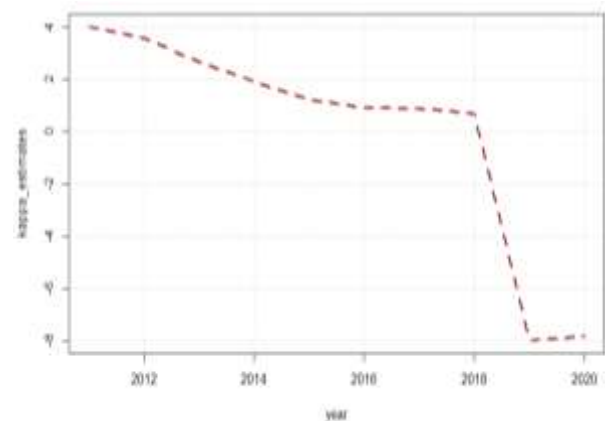


Figure 3: Graph of estimated kappa parameter κ_t

The parameter κ_t represents the general level of mortality of the population under study at that index year. It is also known as the mortality index tracking the main time pattern on the logarithm scale of mortality for all the ages. κ_t is obtained from the vector value ($\kappa_t = D_1 V_{t1}$), findings show a downward trend in mortality pattern from 2011 to 2020, reflecting a substantial decline in mortality rates during this period. This is

consistent with global trends in HIV/AIDS mortality, where advancements in ART and improvements in healthcare access have led to significant reductions in mortality rates [24]. The data indicate a reduction of approximately 29.6% in mortality rates between 2011 and 2020, suggesting that Adamawa State has made notable progress in controlling HIV/AIDS-related deaths.

3.2.2. Forecasting the Kappa (κ_t) Component of the Lee-Carter Model

The application of the ARIMA model for forecasting mortality rates reveals that the ARIMA (0,1,0) model provides the best fit for predicting future mortality trends, with no significant fluctuations expected in the κ_t component beyond 2020 (Table 1). The minimum AIC was 47.29, hence it is the best predictive model based on the model selection criteria of AIC for forecasting the κ_t parameter. This forecast aligns with studies that project stable or declining HIV/AIDS mortality rates in regions with effective ART programs [25]. The predicted stability of mortality rates suggests that, if current healthcare practices are maintained or improved, the state is on track to meet the 2030 Sustainable Development Goal (SDG-3) of significantly reducing HIV/AIDS-related deaths.

The plot of the autocorrelation function (Figure 4), shows a significant spike at lag zero that is considered as insignificant in determining the order of the Moving Average (MA) term of the ARIMA model. Hence an MA term of zero and consequently, the drift parameter θ is also zero since it is accounted for by the order of the MA term. The plot of the partial autocorrelation function shows no significant spike at any lag in the lifetime of the series. This implies an AR term of order zero in the ARIMA model. Hence, the

best fit for the kappa values can also be determined by examining the partial autocorrelation factor (PACF) and the autocorrelation factor (ACF) plots alone.

Table 1: Summary of the best ARIMA models

Model	Sigma squared	AIC
ARIMA(2, 1, 1)	7.953	52.95
ARMA(2, 1, 0)	8.953	51.28
ARIMA(1, 1, 1)	8.976	51.29
ARIMA(0, 1, 1)	8.976	49.29
ARIMA(0, 1, 0)	8.976	47.29
ARIMA(1, 1, 0)	8.976	49.29

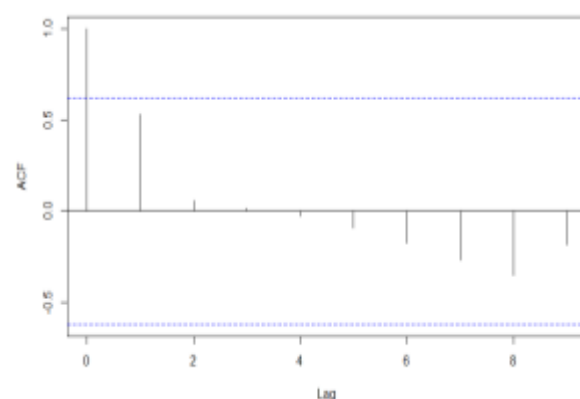


Figure 4: Autocorrelation function: series κ_t estimates

In forecasting the future mortality rates of the Lee-Carter model the equation (5) is employed and only the κ_t parameter is forecasted. The forecast of the parameter estimates is presented in Table 2 which shows the forecasted values of the time component of the LC model base on the ARIMA(0,1,0).

$$\kappa_t = \kappa_{t-1} + \theta + \varepsilon_t \quad (9)$$

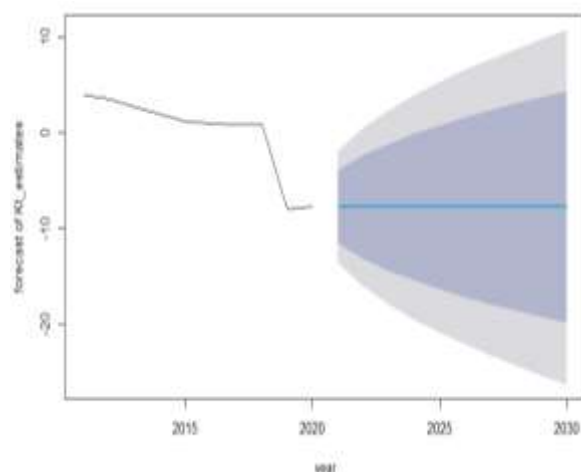
Table 2: Forecast of the kappa value

Year	Point Forecast	Lo80	Hi80	Lo95	Hi95
2021	-7.813	-11.653	-3.9734	-13.685	1.94080
2022	-7.813	-13.243	-2.3829	-16.117	0.49154
2023	-7.813	-14.463	-1.1626	-17.984	2.35793
2024	-7.813	-15.492	-0.1338	-19.557	3.93137
2025	-7.813	-16.399	0.77265	-20.944	5.31761
2026	-7.813	-17.218	1.59211	-22.197	6.57085
2027	-7.813	-17.972	2.34568	-23.349	7.72334
2028	-7.813	-18.673	3.04708	-24.422	8.79604
2029	-7.813	-19.332	3.70585	-25.429	9.80354
2030	-7.813	-19.955	4.32893	-26.382	10.7565

Table 3: Death rate forecast $[exp(\alpha_x + \beta_x k_t)]$

Year	Age Groups								
	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59
2021	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2022	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2023	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2024	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2025	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2026	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2027	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2028	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2029	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2030	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007

Figure 5 shows the plot of the forecasted kappa values base on the ARIMA(0,1,0) which is the model with the minimum AIC and hence the best fit for the kappa values.

**Figure 5:** The plot of forecast value from ARIMA(0,1,0)

Death Rates Forecast

The forecast of death rate is obtained from the equation of the Lee-Carter model;

$$\ln m_{x,t} = \alpha_x + \beta_x k_t \quad (10)$$

From Table 3, the point forecast of the general level of mortality k_t is constant throughout the years. This is because the drift parameter θ is zero because of the MA term of zero in the ARIMA (0,1,0), hence constant k_t . However, all the other age component parameters are varying depending on a group as can be seen in Figure 1.

Table 3 present the age-specific death rate forecast of HIV/AIDS mortality from 2021 to 2030. The forecast indicates a declining mortality rate across all age groups.

This study investigated the possibility of bringing to end the epidemic attributed to HIV/AIDS in Adamawa State within the stipulated deadline, by examining the death rates of PLHIV. The findings of this study are consistent with other research on HIV/AIDS mortality, particularly in sub-Saharan Africa. Studies have shown that the introduction of ART has had a profound impact on reducing mortality rates, particularly in regions with high HIV prevalence [19, 21]. The decline in mortality rates observed in Adamawa State mirrors similar patterns seen in countries like South Africa and Uganda, where widespread ART distribution has significantly reduced AIDS-related deaths [25].

However, despite these positive trends, the higher mortality rates among older populations observed in this study remain a challenge. Studies suggest that older HIV-positive individuals require more comprehensive care, including management of comorbidities and age-related health issues [23]. These findings highlight the need for targeted interventions for older PLHIV, as well as continued efforts to reduce stigma and improve healthcare access for all age groups.

4. Conclusion

This study confirms a sustained decline in HIV-related mortality in Adamawa State and projects a continued downward trend if current treatment efforts are maintained, indicating that the state is generally on track toward improved HIV outcomes. However, older people living with HIV

remain at comparatively higher risk, highlighting the need for more targeted age-specific interventions. The study contributes sub-national mortality estimates using the Lee-Carter framework, offering evidence that can support local HIV planning. Nonetheless, the findings should be interpreted with caution due to limitations such as the short data span, the focus on ART-registered patients, the single-state scope, and assumptions embedded in the modelling approach.

Authors' Contributions

The study was conceptualized and designed by W.N.B. Data collection and experimental work were primarily carried out by W.N.B., H.S., and U.A.A. Data analysis and interpretation were done by W.N.B., H.S., and U.A.A. Manuscript drafting was led by W.N.B. and H.S., with contributions from U.A.A. and R.M.S. Literature review and background development were supported by F.J.S. and R.M.S. All authors reviewed and approved the final manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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References

- [1] J. A. Odugbesan and H. Rjoub, "Relationship among HIV/AIDS Prevalence, Human Capital, Good Governance, and Sustainable Development: Empirical Evidence from Sub-Saharan Africa," *Sustainability*, vol. 11, no. 5, p. 1348, 2019, <https://doi.org/10.3390/su11051348>.
- [2] J. A. Odugbesan and H. Rjoub, "Evaluating HIV/Aids prevalence and sustainable development in sub-Saharan Africa: the role of health expenditure," *African Health Sciences*, vol. 20, no. 2, pp. 568-578, 2020, <https://doi.org/10.4314/ahs.v20i2.4>.
- [3] E. Ukaegbu, R. Alibekova, S. Ali, B. Crape, and A. Issanov, "Trends of HIV/AIDS knowledge and attitudes among Nigerian women between 2007 and 2017 using Multiple Indicator Cluster Survey data," *BMC Public Health*, vol. 22, no. 1, p. 440, 2022/03/04 2022, <https://doi.org/10.1186/s12889-022-12865-y>.
- [4] J. Jones, P. S. Sullivan, and J. W. Curran, "Progress in the HIV epidemic: Identifying goals and measuring success," *PLOS Medicine*, vol. 16, no. 1, p. e1002729, 2019, <https://doi.org/10.1371/journal.pmed.1002729>.
- [5] Y. Assefa and C. F. Gilks, "Ending the epidemic of HIV/AIDS by 2030: Will there be an endgame to HIV, or an endemic HIV requiring an integrated health systems response in many countries?," *International Journal of Infectious Diseases*, vol. 100, pp. 273-277, 2020/11/01/ 2020, <https://doi.org/10.1016/j.ijid.2020.09.011>.
- [6] Q. Liu, C. Ling, D. Li, and L. Peng, "Bias-Corrected Inference for a Modified Lee-Carter Mortality Model," *ASTIN Bulletin*, vol. 49, no. 2, pp. 433-455, 2019, <https://doi.org/10.1017/asb.2019.9>.
- [7] Y. Chen and A. Q. M. Khaliq, "Comparative Study of Mortality Rate Prediction Using Data-Driven Recurrent Neural Networks and the Lee-Carter Model," *Big Data and Cognitive Computing*, vol. 6, no. 4, p. 134, 2022, <https://doi.org/10.3390/bdcc6040134>.
- [8] L. Safitri, S. Mardiyati, and H. Rahim, "Estimation of mortality rate in Indonesia with Lee-Carter model," *AIP Conference Proceedings*, vol. 2023, no. 1, 2018, <https://doi.org/10.1063/1.5064207>.
- [9] Y. R. Safitri, S. Mardiyati, and M. Malik, "The Cairns-Blake-Dowd model to forecast Indonesian mortality rates," *AIP Conference Proceedings*, vol. 2168, no. 1, 2019, <https://doi.org/10.1063/1.5132466>.
- [10] M. Fajar and E. Fajariyanto, "Lee-Carter Modeling for Mortality in Indonesia with A Bayesian Approach," *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 16, no. 4, pp. 1241-1248, 2022, <https://doi.org/10.30598/barekengvol16iss4pp1241-1248>.

- [11] A. H. A. Zili, S. Mardiyati, and D. Lestari, "Forecasting Indonesian mortality rates using the Lee-Carter model and ARIMA method," *AIP Conference Proceedings*, vol. 2023, no. 1, 2018, <https://doi.org/10.1063/1.5064209>.
- [12] N. S. M. Ibrahim, N. M. Lazam, and S. N. Shair, "Forecasting Malaysian mortality rates using the Lee-Carter model with fitting period variants," *Journal of Physics: Conference Series*, vol. 1988, no. 1, p. 012103, 2021/07/01 2021, <https://doi.org/10.1088/1742-6596/1988/1/012103>.
- [13] A. Nigri, S. Levantesi, M. Marino, S. Scognamiglio, and F. Perla, "A Deep Learning Integrated Lee-Carter Model," *Risks*, vol. 7, no. 1, p. 33, 2019, <https://doi.org/10.3390/risks7010033>.
- [14] M.-P. Bergeron-Boucher and S. Kjærgaard, "Mortality forecasting at age 65 and above: an age-specific evaluation of the Lee-Carter model," *Scandinavian Actuarial Journal*, vol. 2022, no. 1, pp. 64-79, 2022/01/02 2022, <https://doi.org/10.1080/03461238.2021.1928542>.
- [15] R. M. Peres, "Modelling Hospital Admission Rates in São Paulo, Brazil: Lee-Carter Model Vs. Neural Networks," Universidade de Lisboa (Portugal), 2022.
- [16] A. Debón, S. Haberman, F. Montes, and E. Otranto, "Do Different Models Induce Changes in Mortality Indicators? That Is a Key Question for Extending the Lee-Carter Model," *International Journal of Environmental Research and Public Health*, vol. 18, no. 4, p. 2204, 2021. [Online]. Available: <https://www.mdpi.com/1660-4601/18/4/2204>.
- [17] H. Booth, R. J. Hyndman, L. Tickle, and P. De Jong, "Lee-Carter mortality forecasting: a multi-country comparison of variants and extensions," *Demographic research*, vol. 15, pp. 289-310, 2006.
- [18] R. D. Lee and L. R. Carter, "Modeling and forecasting US mortality," *Journal of the American statistical association*, vol. 87, no. 419, pp. 659-671, 1992.
- [19] E. J. Mills *et al.*, "Life expectancy of persons receiving combination antiretroviral therapy in low-income countries: a cohort analysis from Uganda," *Annals of internal medicine*, vol. 155, no. 4, pp. 209-216, 2011, <https://doi.org/10.7326/0003-4819-155-4-201108160-00358>.
- [20] N. Ren *et al.*, "Patterns of HIV or AIDS mortality among older people from 1990 to 2019 in China: age-period-cohort analysis," *JMIR Public Health and Surveillance*, vol. 8, no. 11, p. e35785, 2022, <https://doi.org/10.2196/35785>.
- [21] M. Smit *et al.*, "Future challenges for clinical care of an ageing population infected with HIV: a modelling study," *The Lancet Infectious Diseases*, vol. 15, no. 7, pp. 810-818, 2015, [https://doi.org/10.1016/S1473-3099\(15\)00056-0](https://doi.org/10.1016/S1473-3099(15)00056-0).
- [22] A. J. Rodger *et al.*, "Mortality in well controlled HIV in the continuous antiretroviral therapy arms of the SMART and ESPRIT trials compared with the general population," *AIDS*, vol. 27, no. 6, pp. 973-979, 2013, <https://doi.org/10.1097/QAD.0b013e32835cae9c>.
- [23] G. Guaraldi *et al.*, "Premature Age-Related Comorbidities Among HIV-Infected Persons Compared With the General Population," *Clinical Infectious Diseases*, vol. 53, no. 11, pp. 1120-1126, 2011, <https://doi.org/10.1093/cid/cir627>.
- [24] UNAIDS. "Global HIV & AIDS Statistics — 2020 Fact Sheet." <https://www.unaids.org/en/resources/fact-sheet> (accessed 12/06/2024).
- [25] M. I. Mahy, K. M. Sabin, A. Feizzadeh, and I. Wanyeki, "Progress towards 2020 global HIV impact and treatment targets," *Journal of the International AIDS Society*, vol. 24, no. S5, p. e25779, 2021, <https://doi.org/10.1002/jia2.25779>.