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Original Article

Forecasting Years Lived in Poor Health in Kenya: A Comparative Analysis of ARIMA and LSTM Models with Implications for East African Health Policy

Andrew Karani[1] & Dr. Ren Dongxiao[1]*

[1] Zhejiang University of Science and Technology, 318 Liuhe Rd, Xihu, Hangzhou, Zhejiang, China.
*Author for Correspondence ORCID ID; https://orcid.org/0009-0001-9929-5659; Email: karanimwongera@gmail.com

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ABSTRACT

Kenya's life expectancy increased from 55.5 to 64.7 years (1990-2024), but years lived in poor health (GAP) have not declined proportionally, creating substantial public health planning challenges. Evidence-based forecasting of GAP trends is essential for health system resource allocation, yet no systematic forecasting methodologies exist for East African health systems. This study compared ARIMA and LSTM forecasting models for predicting Kenya's GAP trends and established methodological frameworks for health system planning across East Africa. Comparative time series analysis was conducted using Global Burden of Disease Study 2021 data spanning 1990-2021 for Kenya, Uganda, and Tanzania health systems, with 32 annual observations for each country. ARIMA and LSTM models were developed and validated using identical specifications, with performance evaluated using RMSE, MAE, and Diebold-Mariano statistical tests for significance. ARIMA significantly outperformed LSTM in Kenya (RMSE: 5.67 vs 6.66, $p<0.001$), reflecting stable health system patterns suitable for systematic planning, while LSTM demonstrated superior performance in Uganda (RMSE: 8.47 vs 15.03) and Tanzania (RMSE: 7.30 vs 10.10), indicating more complex health dynamics requiring sophisticated modelling approaches. Kenya's predictable GAP patterns enable reliable ARIMA-based forecasting for health system planning, while regional variations necessitate context-specific methodological approaches across East African health systems. This study provides the first systematic GAP forecasting framework for East Africa, offering health policy makers evidence-based tools for resource allocation while establishing methodological foundations for public health planning that can strengthen health systems across the region.

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INTRODUCTION

Kenya's health system, like those throughout East Africa, has achieved remarkable progress in extending life expectancy over the past three decades. Life expectancy in Kenya increased from 55.5 years in 1990 to 64.7 years in 2024, reflecting substantial investments in healthcare infrastructure, disease control programs, and public health interventions (Alwago, 2023; Njenga & Kipchirchir, 2024). However, this epidemiological success story reveals a concerning pattern: while Kenyans are living longer, a significant portion of these additional years is spent in poor health, creating what researchers term the "GAP" - the difference between overall life expectancy and healthy life expectancy (HALE)(Cao et al., 2020). This GAP represents a critical policy challenge that demands evidence-based forecasting to inform health system planning and resource allocation across the region.

The GAP represents years lived with disability, chronic illness, or significant health limitations that affect quality of life and productivity (Martinez et al., 2021; Robine et al., 1999; Tokudome et al., 2016). In Kenya, this indicator has averaged 6.76 years over the past three decades, peaking at 9.32 years in 2004 before declining to more manageable levels through targeted health interventions (Naghavi et al., 2024; Njenga & Kipchirchir, 2024; World Health Organization (WHO), 2023). Understanding and predicting GAP trends is crucial for Kenya's health system planning, as these years of poor health drive demand for chronic disease management, rehabilitation services, and long-term care, which require substantial resource allocation and strategic planning (Moses et al., 2021; Nyawira et al., 2023).

Despite the policy importance of GAP trends, limited research has focused on forecasting this critical health indicator, particularly in African contexts. Traditional statistical methods like Autoregressive Integrated Moving Average (ARIMA) models have proven effective for demographic forecasting in stable contexts, while newer machine learning approaches such as Long Short-Term Memory (LSTM) networks show promise for capturing complex, non-linear health patterns (Cerqueira et al., 2020; Elsaraiti & Merabet, 2021; Kontopoulou et al., 2023; Siami-Namini et al., 2018). The debate between ARIMA and LSTM as effective time series forecasting methods has been explored extensively in various domains, including healthcare. ARIMA, a traditional statistical approach, is valued for its simplicity, interpretability, and robust performance in structured, linear time series data. However, it struggles to capture nonlinear and complex dependencies, which are increasingly relevant in healthcare predictions (Li, 2024; Sirisha et al., 2022). Conversely, LSTM, a deep learning model, excels in modelling nonlinear relationships and

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long-term dependencies, demonstrating superior predictive accuracy in complex scenarios such as mortality forecasting, disease burden analysis, and life expectancy estimation (Esteban et al., 2016; Garrido et al., 2024; Sherstinsky, 2020; Tsantekidis et al., 2022; T. Wang et al., 2020). However, no systematic comparison has evaluated which approach best captures GAP dynamics in Kenya or similar East African health systems.

The primary objective is to determine whether traditional ARIMA or advanced LSTM methods more accurately forecast Kenya's GAP trends, thereby informing health system resource allocation and strategic planning. Secondary objectives include contextualising Kenya's patterns within East African regional trends and developing policy recommendations for health system strengthening based on forecasting results. These findings will directly support Kenya's health sector strategic planning while providing a methodological framework for GAP forecasting across East Africa.

Kenya Health System Context

Kenya's health system provides an ideal context for GAP forecasting methodology development due to several unique characteristics that distinguish it within the East African region. Firstly, Kenya's relative political stability since the 2010 constitutional reforms has enabled sustained health policy implementation, creating more predictable health trend patterns compared to countries experiencing frequent policy disruptions (Hyden & Onyango, 2021). This stability is reflected in consistent health sector budget allocations and sustained implementation of major health programs such as the Health Sector Strategic Plan and Universal Health Coverage initiatives (Neumark & Prince, 2021).

Secondly, Kenya possesses East Africa's most comprehensive health information system, with robust vital registration and disease surveillance capabilities that generate high-quality longitudinal health data (Odeny et al., 2023). The Kenya Health Information System (KHIS) and collaboration with international health monitoring initiatives provide reliable data streams essential for accurate forecasting model development (Nyangena et al., 2021).

Thirdly, Kenya has successfully navigated the epidemiological transition from a predominantly infectious disease burden to increased non-communicable disease prevalence, making it a regional leader in managing the health challenges that drive GAP increases (Mtintsilana et al., 2023; Neumark & Prince, 2021). This transition experience provides valuable insights for forecasting future health needs and resource requirements across East Africa.

METHODS

Study Design and Rationale

This study employs a comparative time series forecasting approach to evaluate optimal methods for predicting Kenya's GAP trends, with cross-validation using Uganda and Tanzania data to contextualise findings within the East African health landscape. The primary focus on Kenya leverages the country's robust health data systems and relative political stability, which provide ideal conditions for developing reliable forecasting methodologies that can inform evidence-based health policy across the region.

Data Sources and Quality Assessment

The study utilises comprehensive health data from two authoritative sources: the Global Burden of Disease Study 2021 (GBD 2021) and WHO estimates of HALE. For Kenya, the primary focus country, we extracted annual data spanning 1990-2021 (32 observations), including life expectancy at birth (LE), healthy life expectancy (HALE), and derived GAP calculations. To contextualise Kenya's forecasting results within the broader East African health landscape, we included comparable time series data from Uganda and Tanzania (1990-2021). This comparative approach enables assessment of

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whether forecasting model performance varies across different East African health system contexts, thereby informing regional health planning strategies.

The GAP serves as the primary outcome variable and was calculated as:

$$GAP = Life\ Expectancy\ at\ Birth\ (LE_0) - Healthy\ Life\ Expectancy\ (HALE)$$

This indicator represents the average number of years individuals in a population can expect to live with significant health limitations, disability, or chronic disease burden (Cao et al., 2020; Labbe, 2010; Permanyer & Bramajo, 2023; Tokudome et al., 2016).

Methodological Framework

The analysis employs a two-phase comparative modeling approach, with primary focus on developing optimal forecasting methods for Kenya's health planning needs. Phase 1 will be the Kenya-focused model development, which involves determining optimal forecasting methodology for Kenya's GAP trends to support national health system planning and resource allocation. Phase 2 involves validating methodological findings using Uganda and Tanzania data to assess generalizability and inform regional health planning approaches.

Traditional Statistical Method: ARIMA

The ARIMA model is a parametric statistical approach widely used in time series analysis and forecasting, particularly suited for contexts with stable underlying trends (Li, 2024; Majidnia et al., 2023). ARIMA modelling follows the Box-Jenkins methodology: (1) stationarity assessment using the ADF test, (2) parameter selection via AIC/BIC criteria, and (3) residual diagnostics using the Ljung-Box Q statistic. The Ljung-Box Q statistic is as follows:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{{\rho_k}^2}{n-k}$$

Where n is the sample size, m is the number of lags, and ρ_k is the autocorrelation at lag k (Kim et al., 2004). The optimal ARIMA(p,d,q) model captures autoregressive, differencing, and moving average components.

Advanced Machine Learning Method: LSTM

Forecasting with non-parametric models, particularly neural networks, has revolutionised time series analysis by addressing the limitations of traditional parametric models like ARIMA. Neural networks excel at modelling complex, nonlinear relationships in data. Among these, RNNs and their advanced variant, LSTM networks, are particularly effective for sequential data such as time series. These models can capture dependencies across time, including short-term and long-term patterns (T. Wang et al., 2020; Zhang et al., 2022).

LSTM networks utilise gating mechanisms (forget, input, output gates) to capture long-term dependencies in sequential data. The gating mechanisms enable LSTMs to retain information over extended sequences, making them ideal for datasets with long-term patterns (Garrido et al., 2024; Tsantekidis et al., 2022). The model was implemented with two LSTM layers (50 units each), dropout regularization (20%), and Adam optimizer with Mean Squared Error (MSE) loss function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Performance Metrics

After training the ARIMA and LSTM models, the forecasting process involved using the finalised models to predict future GAP values. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics were then used to evaluate the performance of these forecasts. To statistically compare the accuracy of ARIMA and LSTM

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forecasts, the Diebold-Mariano (DM) test was conducted. The DM test evaluates whether the forecasting errors from two models are significantly different, using the null hypothesis that the models have equal forecast accuracy (Zhou et al., 2021). The test statistic is calculated as:

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}}$$

Where $\bar{d}$ is the mean of the loss differential $d_t = g(e_{1t}) - g(e_{2t})$, $\hat{f}_d(0)$ is the spectral density of d_t at frequency zero, and T is the sample size. Here, $g(\cdot)$ is a loss function, such as squared error, and e_{1t} , e_{2t} are the forecast errors from ARIMA and LSTM, respectively. For each country, both ARIMA and LSTM models were implemented using identical methodological specifications, enabling direct performance comparison and regional pattern identification.

Data Ethics and Limitations

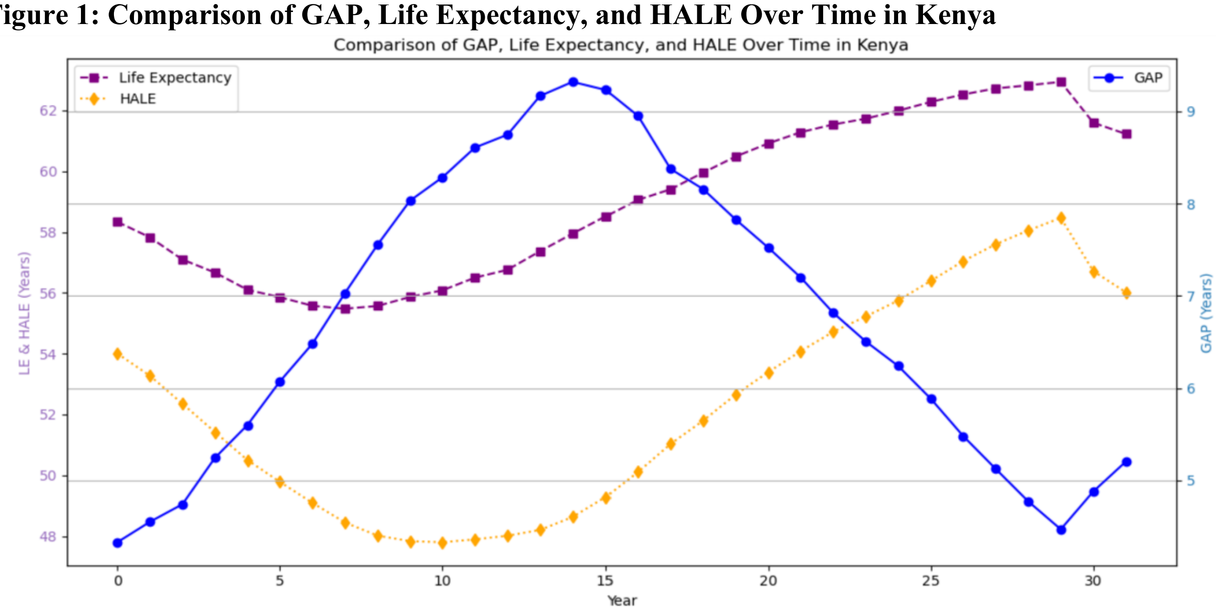
All data utilised in this study derive from publicly available, aggregate-level health statistics from internationally recognised sources (Institute for Health Metrics and Evaluation (IHME), 2021; World Health Organization (WHO), 2023). No individual-level data or personally identifiable information was accessed or analysed. The 32-year observation period, while spanning meaningful health development phases, represents a modest sample size for machine learning applications, particularly LSTM networks, which typically benefit from larger datasets (Mienye et al., 2024). The analysis is limited to the 1990-2021 period based on data availability, potentially missing longer-term cyclical patterns in health trends. In addition, while Kenya provides an excellent case study for East African health forecasting, generalizability to other African regions or global contexts requires additional validation.

RESULTS

Kenya Gap Trends and Health Dynamics

Kenya's GAP averaged 6.76 years (1990-2021), peaking at 9.32 years (2004) and declining to current levels around 6.2 years. This decline coincided with major health sector reforms and sustained policy implementation between 2005-2015.

Figure 1: Comparison of GAP, Life Expectancy, and HALE Over Time in Kenya



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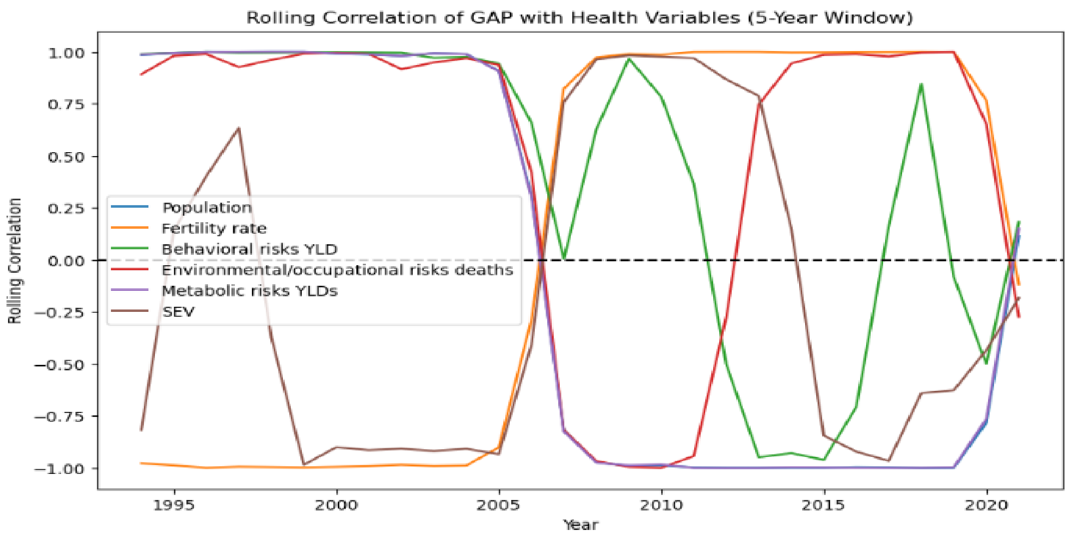
The rolling correlation analysis provides insights into how the relationships between GAP and the other variables have evolved from 1990 to 2021. A rolling window of 5 years was chosen to smooth short-term fluctuations and highlight long-term trends. This approach helps account for policy changes, economic shifts, and healthcare advancements that may not be evident in year-to-year data. Figure 2 reveals some variables, such as metabolic risks, YLDs, and environmental/ occupational risks deaths, generally maintain strong positive correlations with GAP, suggesting a persistent link. Behavioural risks YLD and SEV show periods of strong positive and negative correlations, indicating evolving influences on GAP over time.

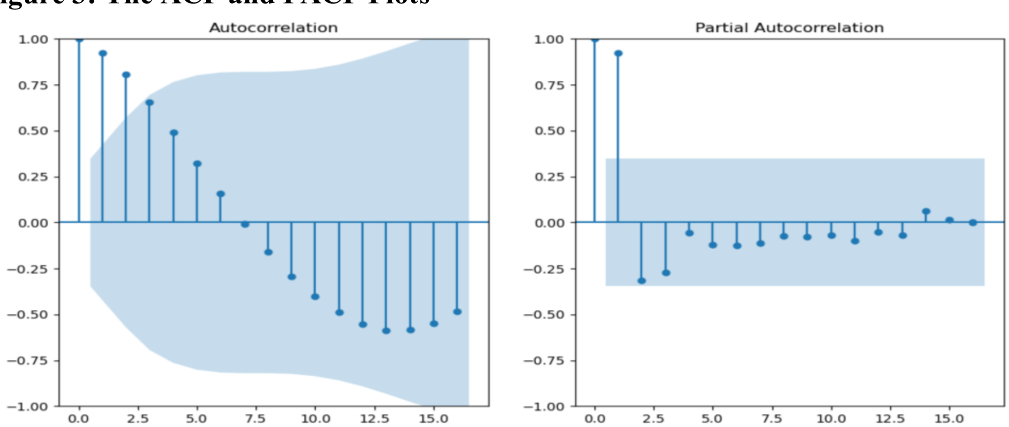
Figure 2: Rolling Correlation of GAP with Health Variables (5-Year Window)



The transitions around 2005 and 2015 suggest significant structural or policy-driven shifts. However, the most notable change was around the mid-2000s when many variables experienced sudden correlation reversals, possibly due to major economic or health-related shifts.

Model Development and Performance

Figure 3: The ACF and PACF Plots



ARIMA Model Implementation

The ADF test confirmed stationarity (ADF = -3.4752, p = 0.009), eliminating the need for differencing (d = 0). ACF and PACF analysis indicated an AR(1) process (sharp PACF cutoff at lag 1) and an MA(3) process (gradual ACF decline to lag 3), suggesting ARIMA(1,0,3).

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Model selection using AIC and BIC criteria identified ARIMA(1,0,3) as optimal (AIC = -0.558, BIC = 8.236). Ljung-Box testing confirmed adequate model fit with no significant residual autocorrelation (Q = *0.17, p = 0.995).*

The fitted model equation is:

$$\begin{aligned} GAP_{Kenya,t} = \ & 5.6851 + 0.9451y_{t-1} + \epsilon_t \\ & + 0.8338\epsilon_{t-1} + 1.126\epsilon_{t-2} \\ & + 0.4706\epsilon_{t-3} \end{aligned}$$

The significant autoregressive coefficient (φ_1 = 0.945) indicates strong GAP persistence, while the constant term (μ = 5.685) centres predictions around 5.7 years. Moving average terms demonstrate extended shock effects: MA(1) and MA(2) show substantial impact from recent disturbances, while MA(3) indicates weaker but persistent effects from policy shifts or health system changes.

LSTM Model Implementation

The dataset was split into training (25 points) and testing (7 points) sets. Data preprocessing included MinMaxScaler normalization (0-1 range) and sequence structuring for temporal dependencies. The LSTM architecture comprised two LSTM layers (50 units each) with 20% dropout regularization to prevent overfitting, followed by a dense output layer. The model was trained for 100 epochs using the Adam optimizer with an MSE loss function and a batch size of 8.

Figure 4: Loss Function Results for the LSTM Model

```
3/3 - 0s - 19ms/step - loss: 0.0158
Epoch 93/100
3/3 - 0s - 19ms/step - loss: 0.0118
Epoch 94/100
3/3 - 0s - 20ms/step - loss: 0.0198
Epoch 95/100
3/3 - 0s - 19ms/step - loss: 0.0166
Epoch 96/100
3/3 - 0s - 19ms/step - loss: 0.0185
Epoch 97/100
3/3 - 0s - 22ms/step - loss: 0.0126
Epoch 98/100
3/3 - 0s - 23ms/step - loss: 0.0168
Epoch 99/100
3/3 - 0s - 22ms/step - loss: 0.0150
Epoch 100/100
3/3 - 0s - 17ms/step - loss: 0.0139
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step
```

The loss function demonstrates successful model convergence, with gradual decline across epochs and stabilisation at 0.0139, indicating effective learning of GAP patterns.

ARIMA and LSTM Predictions Comparisons

The ARIMA model demonstrated superior forecasting performance compared to LSTM, achieving lower error rates across all evaluation metrics with RMSE of 5.67 versus 6.66 for LSTM and MAE of 5.67 versus 6.65 for LSTM, representing a 14.8% improvement in prediction accuracy.

Statistical significance of the performance differences was assessed using the Diebold-Mariano test. The DM statistic of -45.30 (p-value = 9.90e-08) provided strong evidence rejecting the null hypothesis of equal forecast accuracy, confirming that ARIMA's superior performance is statistically significant ($p<0.001$) in forecasting Kenya's GAP values.

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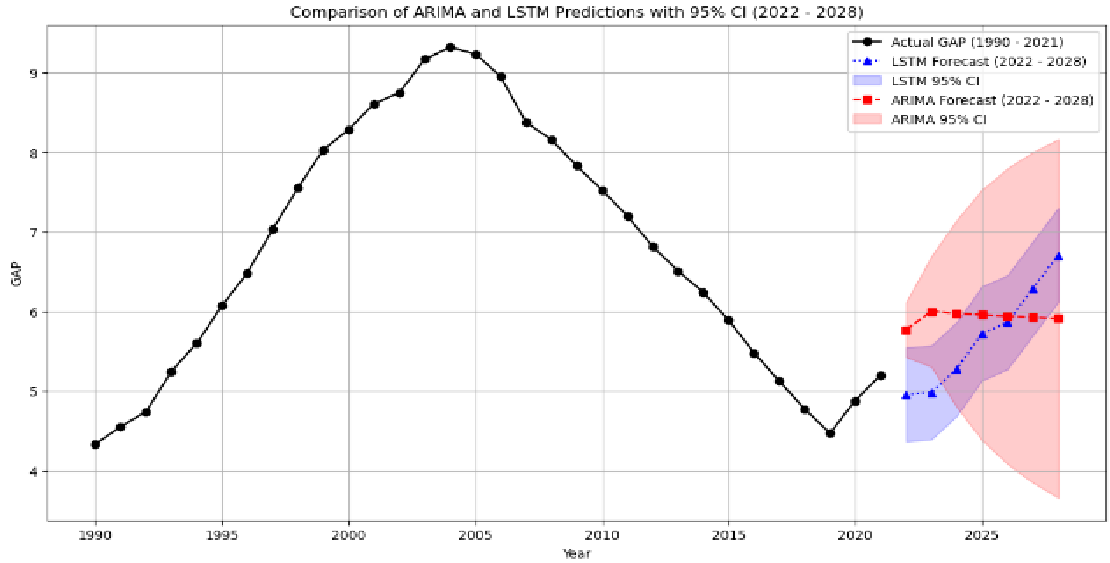
Figure 5. Comparison of ARIMA and LSTM Predictions with 95% CI



Both models project increasing GAP trends, but with notably different trajectories. LSTM forecasts a steep, rapid increase after 2025 with narrow confidence intervals, while ARIMA predicts a more gradual, stable progression with broader confidence intervals that widen over time. This pattern reflects ARIMA's tendency toward stationarity-based projections and demonstrates greater forecasting uncertainty in extended time horizons, which is typical for traditional time series models (Sirisha et al., 2022; X. Wang et al., 2023).

Regional Comparative Context

The two models were further assessed across three countries, Kenya, Uganda, and Tanzania, using similar performance metrics. The results are as shown in Table 1 below.

Table 1: Multi-country Comparison of the Performance Metrics

Country	ARIMA RMSE	LSTM RMSE	DM Test Stat	DM P value
Kenya	5.673	6.659	-45.300	9.90E-08
Uganda	15.027	8.470	-128.300	5.39E-16
Tanzania	10.103	7.300	-163.584	6.06E-17

Regional validation across Uganda and Tanzania reveals important methodological insights for East African health system development. While Kenya's stable patterns favour traditional ARIMA approaches, Uganda (LSTM RMSE: 8.47 vs ARIMA: 15.03) and Tanzania (LSTM RMSE: 7.30 vs ARIMA: 10.10) require more sophisticated modelling to capture complex health dynamics. This differential performance suggests that Kenya's health system stability creates opportunities for systematic planning approaches that may be premature in neighbouring countries still experiencing more volatile health development patterns.

DISCUSSION

This study provides Kenya's health policy makers with the first systematic evaluation of GAP forecasting methodologies, demonstrating that traditional ARIMA modeling significantly outperforms advanced machine learning approaches for Kenya's health system planning needs. The

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superior ARIMA performance (RMSE: 5.67 vs 6.66 for LSTM, $p<0.001$) reflects Kenya's achievement of health system stability that enables systematic, evidence-based planning approaches, distinguishing the country within the East African regional context.

Kenya's GAP data exhibits smoother trends with predictable patterns that align with ARIMA's strengths in capturing linear trends and stable behaviours, making it well-suited for datasets with minimal abrupt changes. Conversely, the superior LSTM performance in Uganda and Tanzania suggests their GAP data contains complex, non-linear trends that LSTM's neural network architecture effectively captures through its ability to model long-term dependencies. The statistically significant differences across all three countries (DM test p-values <0.001) confirm that ARIMA's advantage in Kenya and LSTM's superior performance in Uganda and Tanzania represent meaningful methodological insights for regional health planning.

Policy Implications for Kenya's Health System Development

Kenya should immediately integrate routine GAP forecasting into health sector strategic planning, leveraging ARIMA methodology's demonstrated reliability for evidence-based resource allocation. The projected gradual increase creates opportunities for systematic capacity building in chronic disease management, requiring approximately 15-20% expansion in long-term care infrastructure over the next decade. This forecasting success positions Kenya for regional health system leadership through establishing an East African Health Forecasting Initiative, providing technical assistance to neighbouring countries while building regional capacity for evidence-based health planning that strengthens health security across East Africa.

CONCLUSION

The projected GAP increases across East Africa signal a growing morbidity burden, indicating that while populations live longer, substantial portions of additional years are spent in poor health. This trend suggests increased non-communicable disease prevalence, prolonged disability, and inadequate preventive healthcare access, potentially translating into higher healthcare costs, reduced workforce productivity, and broader socio-economic strain in resource-constrained settings.

This study demonstrates that Kenya's stable health development trajectory enables reliable GAP forecasting through traditional ARIMA methodology, providing health policy makers with evidence-based tools for systematic health system planning. The differential performance patterns across East African countries reveal opportunities for regional collaboration that leverages Kenya's methodological success while addressing diverse health system contexts. For Kenya's health sector strategic planning, these findings support immediate GAP forecasting integration into routine planning processes and position Kenya for regional leadership in evidence-based health system development.

Study Limitations and Future Directions

The 32-year time series represents a modest sample size that limits forecasting confidence beyond 5-7 years. Future research should expand to subnational analysis within Kenya, incorporate external health determinants, and validate methodological approaches across additional African contexts. While aggregate national data suits strategic planning, it doesn't address subnational variations relevant for targeted interventions within Kenya's devolved health system. Future studies should explore combining ARIMA's linear forecasting strengths with LSTM's nonlinear capabilities to develop hybrid models with enhanced predictive accuracy.

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Competing Interests: The authors declare no competing interests.

Ethics Statement: This study utilised publicly available, aggregate-level health statistics. No individual-level data or personally identifiable information was accessed or analysed. Ethical approval was not required for this secondary data analysis.

Data Availability: Data used in this analysis are publicly available from the Global Burden of Disease Study 2021 (http://ghdx.healthdata.org/) and World Health Organization databases (https://www.who.int/data/collections).

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