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Reducing Forecast Errors in HIV Test Kit Quantification Using Region-Specific Models: A Mixed-Methods Analysis of Routine Data from Zambia

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Abstract

Background: Accurate quantification of human immunodeficiency virus (HIV) test kits is essential for ensuring uninterrupted testing services and achieving HIV control targets. In Zambia, quantification is largely conducted using national-level approaches that may not adequately capture regional variations in the demand for testing. This study assessed regional differences in HIV testing patterns and evaluated the need for region-specific approaches to quantify HIV test kits in Zambia. **Methods:** This convergent parallel mixed-methods study combined longitudinal consumption data from 517 health facilities (2020-2024) with qualitative insights from eight key informants. A retrospective analysis was conducted using routine program data on HIV testing and test kit consumption across three Zambian provinces. A regionalised exponential smoothing with trend and seasonality (REST-S) model was developed with province-specific parameters for distinct epidemiological and operational contexts. Data from 2020 to 2024 were used to assess the testing volume, positivity rates, and consumption patterns. Comparative analyses across regions evaluated discrepancies between estimated and actual consumption to identify inefficiencies in the quantification approaches. The forecast accuracy was assessed using the mean absolute percentage error (MAPE). Qualitative themes were numerically coded and correlated with quantitative performance using Spearman's rank correlation. **Results:** Substantial regional variations in HIV testing demand and test kit consumption were observed across provinces. High-burden regions demonstrated consistently higher testing volumes and positivity rates, whereas low-burden regions exhibited fluctuating demand patterns. Provincial consumption patterns diverged substantially from the national forecasts. Lusaka consumed 44% more than allocations (95% CI: +38.2% to +49.8%), while Copperbelt exhibited the highest volatility (coefficient of variation = 42.3%, CAGR 22.2%). The current national forecasting model produced large forecasting errors across all provinces (weighted average MAPE 28.7%, 95% CI: 25.1% - 32.5%), exceeding the WHO error thresholds. The REST-S model achieved a 62% - 76% error reduction, with the MAPE declining to 6.8% - 12.5% across provinces. Diebold-Mariano tests confirmed superior predictive accuracy ($p < 0.001$). A strong correlation (Spearman's $\rho = 0.87$, $p = 0.015$) between quantitative forecast errors and qualitative assessments of operational challenges validated the model performance. The use of uniform national forecasting approaches resulted in overestimation in some provinces and underestimation in others, contributing to stock imbalances, including both stockouts and overstocking. These inefficiencies highlight the limitations of the current centralised forecasting model. **Conclusion:** Region-specific forecasting approaches to HIV test kit quantification can improve forecasting accuracy and enhance supply chain efficiency in Zambia. Tailoring forecasting models to regional epidemiological and service delivery patterns could reduce stock imbalances, save limited resources, and support more effective HIV testing programs. Further research should explore the integration of epidemiological, programmatic, and demographic factors into adaptive forecasting models.

Keywords

HIV Testing, Test Kit Quantification, Forecasting, Supply Chain Management, Regional Variation, Routine Program Data, Commodity Security, Zambia

1. Introduction

Rapid HIV testing is fundamental to epidemic control and is central to achieving the 95-95-95 targets, antiretroviral therapy coverage, and viral suppression (Mulenga et al., 2024). Point-of-care (POC) testing technologies facilitate timely linkage to treatment and enable rapid clinical decision-making, particularly in settings with limited laboratory infrastructure (Drain & Rousseau, 2017; Zachary et al., 2012). However, low- and middle-income countries across Sub-Saharan Africa face persistent challenges in accurately forecasting health commodity needs (Pradhan et al., 2023). Inaccurate forecasting results in frequent stockouts and inefficient procurement processes that undermine equitable access to essential diagnostic services (Boutayeb, 2010).

Zambia has made significant progress toward the 95-95-95 targets, with 96% of those estimated to be living with HIV aware of their status and 98% on antiretroviral therapy (Mulenga et al., 2024). However, the country exemplifies the complexities of resource allocation within a decentralised health system (Uzoma & Igboanugo, 2021). This is marked by substantial disparities in commodity availability across provinces and districts. Geographic variation in HIV prevalence is pronounced, ranging from 5.8% in the Northern Province to 14.4% in the Lusaka Province, with some districts exceeding the national average by nearly double (Mweemba et al., 2022). Despite national policies aimed at improving commodity availability, frequent stockouts persist for key laboratory reagents and consumables (Nefdt et al., 2014). This is compounded by logistical bottlenecks and infrastructural deficits, which result in inefficient resource distribution (Subramanian, 2021).

National-level forecasting approaches for health commodities often rely on aggregated epidemiological data and uniform allocation formulae. However, this strategy overlooks the substantial geographic and demographic heterogeneity in healthcare demand characteristic of decentralized health systems (Kruk et al., 2018). Similar challenges have been documented across Sub-Saharan Africa, where regional disparities in disease prevalence and health system capacity necessitate tailored approaches to commodity quantification rather than reliance on centralized estimates (Cremin et al., 2012). However, there is limited empirical evidence assessing regional variation in HIV test kit demand and its implications for quantification in Zambia (Azevedo, 2017).

This study is the first to systematically evaluate regional variability in HIV test kit demand and its implications for HIV commodity forecasting in Zambia using routine data.

2. Materials and Methods

2.1. Study Design, Site, and Population

A convergent parallel mixed-methods study was conducted using secondary health facility logistics data (Abowitz & Toole, 2010) on HIV test kit consumption in Zambia from January 2020 to December 2024. Actual facility-level consumption data were compared with national forecasts for HIV Determine test kits, as documented in the approved National HIV Tests Quantification Reports for the period 2020 to 2024. These national forecast estimates were generated using a composite methodology that integrates historical national consumption data, HIV prevalence and incidence rates, and quantities received and issued by the Zambia Medicines and Medical Supplies Agency (ZAMMSA). The resulting aggregated estimates informed national-level forecasts, which underpin supply planning and procurement decisions for HIV test kits.

For this study, national forecast estimates were apportioned to the provincial level by dividing the total forecast by the number of provinces in the country and subsequently disaggregated into monthly estimates by dividing by 12. The resulting monthly provincial forecasts were then compared with the corresponding actual provincial consumption data.

This study integrated quantitative consumption analysis with qualitative stakeholder perspectives to develop and validate a region-specific forecasting model for HIV test kit quantification. Quantitative and qualitative data were collected independently, analysed using their respective methods, and subsequently integrated through triangulation using joint display tables.

Zambia's health system comprises public facilities at multiple levels of care (health posts, health centres, district hospitals, and teaching hospitals) and is overseen by the Ministry of Health. HIV testing services are delivered through a routine program using rapid screening tests (HIV 1/2 Determine) at all levels of care. This study was conducted in three provinces to represent Zambia's epidemiological and socioeconomic diversity (Coombs et al., 2022). Lusaka Province provided the urban context with the highest HIV prevalence and service density, Copperbelt Province provided the peri-urban context with mobile populations and seasonal service variations, and Southern Province provided the rural context with dispersed populations and limited infrastructure. This tri-context sampling strategy ensured that the findings reflected heterogeneous conditions across Zambia's health system (Coombs et al., 2022).

Consumption data for HIV screening test kits (HIV 1/2 Determine) were extracted from the electronic Logistics Management Information System (eLMIS), capturing the actual number of tests conducted at each facility (Mkumbwa et al., 2023). eLMIS is Zambia's national supply chain platform that captures routine program data from all public health facilities supplied by the Zambia Medicines and Medical Supplies Agency (ZAMMSA). The analysis period was restricted to intervals with no reported stockouts at both facility level and central level (ZAMMSA), to ensure that recorded consumption accurately reflected utilization. Furthermore, the selected commodity, Determine HIV test kits, is predominantly donor-funded, thereby minimizing supply constraints and allowing the data to serve as a reliable proxy for true demand.

2.2. Key Variables and Definitions

HIV Test Kit consumption is the actual quantity of HIV 1/2 Determine test kits used monthly at the health facility level, measured in tests (Kim & Kim, 2016).

Forecasting is the process of estimating commodity requirements based on service utilisation patterns, population demographics, and disease burden (Soyiri et al., 2012).

Forecast Mismatch is the discrepancy between estimated (forecasted) consumption and actual observed consumption, expressed as a percentage difference (Hutter & Weber, 2016).

Forecast Error is the error metric calculated as the percentage difference between estimated and actual consumption, calculated as $\left[\left(\text{Forecast} - \text{Actual}\right)/\text{Actual}\right] \times 100$ (Kim & Kim, 2016).

2.3. Sample Size and Selection

A complete enumeration of health facilities across the three provinces was undertaken. The sample size was subsequently determined using Cochran's formula, with eligibility restricted to facilities demonstrating ≥80% monthly reporting completeness (Taye et al., 2023) (100% enumeration, non-random sampling). This comprehensive approach captures all variations in provincial consumption patterns. The data were stratified by facility level (primary, secondary, and tertiary) to ensure the representation of diverse facility types. Specific sample composition—Southern Province (433 facilities, 204 analysed in the quantitative component); Lusaka (345 facilities, 131 analysed), and Copperbelt (345 facilities, 182 analysed). The sample size for the quantitative component was calculated using Cochran's formula, yielding $n = 204$ for Southern Province; similar calculations produced $n = 131$ for Lusaka and $n = 182$ for Copperbelt, giving a census of 517 facilities in this study.

Cochran's formula:

$$n = \frac{N * Z^2 * p * (1-p)}{E^2 * (N-1) + Z^2 * p * (1-p)}$$

where N = Population;

$Z = 1.96$ (for 95% confidence);

$p = 0.5$ (conservative estimate);

$E = 0.05$.

2.4. Inclusion and Exclusion Criteria

The study included active health facilities that were government-owned or supplied through the ZAMMSA, provided they operated continuously throughout the study period and had complete monthly consumption records available. Facilities were excluded if they had more than 20% missing monthly data, experienced discontinuous operation during the study period, or were considered non-representative outliers, such as private clinics not integrated into the national quantification system.

2.5. Data Management and Quality Control

2.5.1. Quantitative Data Quality Procedures

Completeness checks were also performed. Facilities with <80% monthly reporting rates were excluded (Taye et al., 2023). Outliers with values exceeding three standard deviations from the provincial mean were flagged for manual review. The linear interpolation method was used to fill in the missing values between two known data points, assuming a linear change. Logical validation was performed by investigating negative consumption values and impossible spikes (>10× monthly average).

2.5.2. REST-S Model Diagnostic Testing

Residual analysis confirmed that the residuals followed a normal distribution (Shapiro-Wilk test, $p > 0.05$), while Durbin-Watson tests confirmed no significant autocorrelation. Homoscedasticity was visually assessed using residual plots. A Diebold-Mariano test ($p < 0.001$) confirmed the superiority of the REST-S model over the national forecasting model.

2.5.3. Qualitative Data Validation

Member checking was performed by sharing the preliminary findings with three participants to verify their accuracy. Triangulation indicated a correlation between qualitative themes and quantitative performance metrics. Spearman's correlation revealed a strong correlation ($\rho = 0.87$, $p = 0.015$) between forecast errors and qualitative assessments of quantification consistency.

2.6. Data Analysis

2.6.1. Descriptive Analysis

Central tendency measures (mean and median with interquartile ranges) and dispersion measures (standard deviation, coefficient of variation, and range) were calculated for monthly consumption across provinces (Boutayeb, 2010). Trends were examined using compound annual growth rates (CAGRs) with 95% confidence intervals. Seasonality was assessed using multiplicative decomposition with a 12-month moving average. Regional comparisons were performed to identify consumption patterns by facility level and province-wise.

2.6.2. Analytical Methods

The forecast accuracy was evaluated using three metrics. Mean absolute percentage error (MAPE), mean squared error (MSE), and Theil's U statistic. The forecast error was calculated as the percentage difference between the estimated consumption from the forecasting model and the actual observed consumption. Provincial differences in forecast accuracy and consumption patterns were tested using one-way ANOVA, followed by Tukey post hoc comparisons, with effect sizes reported as Cohen's d and partial η^2 (95% CI).

2.6.3. REST-S Forecasting Model

The regionalised exponential smoothing with trend and seasonality (REST-S) model was developed as the primary forecasting method, incorporating three components: level, trend, and seasonality. The model formulation for each province p at time t was as follows:

$$F(t+1) = \alpha \times \text{Consumption}(t) + (1-\alpha)\left[\text{Level}(t-1) + \text{Trend}(t-1)\right] + \text{Seasonal}(t) + \varepsilon$$

where:

α (smoothing parameter) controls responsiveness to recent consumption changes (0.35 - 0.65 range by province);

β (trend component) captures growth patterns reflecting epidemiological expansion or service scale-up (0.20 - 0.40);

γ (seasonality component) adjusts for monthly variations, calibrated independently per province.

2.6.4. Development and Validation of the REST-S Model

1) Model Formulation and Theoretical Basis

The REST-S model was developed and validated using a clearly defined train-test split. The training period spanned 2020-2023 (48 months), while the validation (hold-out) period comprised 20% of the dataset, approximately 12 months (2024) within the five-year time frame. Accordingly, the training dataset included 48 monthly observations per province, and the validation dataset included approximately 12 monthly observations per province. Parameter tuning and model evaluation were conducted on separate datasets. Model parameters were optimized during the training period (2020-2023) by minimizing the mean absolute percentage error (MAPE), and performance was subsequently assessed on the held-out validation data. Distinct parameter sets were estimated for each province, Lusaka ($\alpha = 0.35$, $\beta = 0.25$, $\gamma = 0.30$), Copperbelt ($\alpha = 0.65$, $\beta = 0.40$, $\gamma = 0.35$), and Southern ($\alpha = 0.45$, $\beta = 0.20$, $\gamma = 0.15$). The regionalised exponential smoothing with trend and seasonality (REST-S) model was developed to address the limitations of uniform national forecasting. The model formulation for each province p at time t is as follows:

$$\hat{Y}_{t+1,p} = \alpha_p Y_{t,p} + \left(1-\alpha_p\right)\left(\hat{Y}_{t,p} + T_{t,p}\right) + S_{t,p} + \epsilon_{t,p}$$

where:

- $\hat{Y}_{t+1,p}$ = Forecast for next period;
- $Y_{t,p}$ = Actual consumption in current period;
- α_p = Province-specific smoothing parameter ($0 \le \alpha \le 1$);
- $T_{t,p} = \beta_p \cdot \Delta Y_{t,p}$ = Trend component;
- $S_{t,p} = \gamma_p \cdot \left(Y_{t,p} - \hat{Y}_{t,p}^{D}\right)$ = Seasonal adjustment;
- $\epsilon_{t,p} \sim N\left(0, \sigma_p^2\right)$ = Error term.

The model was selected after a comparative analysis with ARIMA, Holt-Winters, and simple exponential smoothing alternatives, based on the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC) scores.

2) Parameter Calibration Methodology

The parameters were optimised using constrained minimisation of the mean absolute percentage error (MAPE) over the training period (2020-2023).

$$\min_{\alpha_p, \beta_p, \gamma_p} \sum_{t=13}^{48} \left| \frac{Y_{t,p} - \hat{Y}_{t,p}}{Y_{t,p}} \right| \times 100\%$$

Subject to stability constraints: $0 \le \alpha_p, \beta_p, \gamma_p \le 1$ and $\alpha_p + \beta_p + \gamma_p \le 1.5$.

Optimisation was performed using the L-BFGS-B algorithm in Python, with convergence achieved within 50 iterations for all the provinces.

2.6.5. Qualitative Data

Qualitative data were collected through structured key informant interviews and focus group discussions using a pre-developed questionnaire containing open-ended questions that were aligned with the study's objectives. The questionnaire was designed to explore the determinants of HIV test kit demand, challenges affecting quantification accuracy, and opportunities for implementing a regionally specific quantification model. The structured format ensured consistency across respondents while allowing participants to elaborate on the contextual and operational realities.

A purposive sampling strategy was used to recruit individuals with direct expertise in HIV commodity forecasting and supply chain management. Key informants were selected to represent multiple levels of the Zambian public health commodity supply chain. Facility-level participants were recruited from a high-volume urban hospital and a rural district health centre to capture variations in service demand and reporting capacity. Provincial-level participants were drawn from the Southern, Copperbelt, and Lusaka provinces because of their high population densities and complex supply chain dynamics. The national-level participants included senior personnel involved in forecasting, supply planning, and logistics coordination. The participants' professional experience ranged from 2 to 19 years.

Mixed-methods integration required the transformation of qualitative themes into quantitative ordinal scores to enable statistical correlation with forecast outcomes. This conversion followed a systematic and transparent protocol designed to minimize subjectivity, enhance reproducibility, and ensure analytical rigor.

Three overarching themes were identified through deductive-inductive thematic analysis: 1) perceived feasibility of regional quantification, 2) systemic and operational challenges affecting quantification, and 3) strategic recommendations for strengthening decentralized systems. Each theme comprised multiple subthemes and codes capturing distinct dimensions of stakeholder perspectives.

To operationalize these qualitative constructs, a five-point ordinal scale was developed to reflect stakeholder perceptions across two core dimensions: quantification feasibility and implementation readiness. The scale was defined as follows:

Score 1 (Highly Unfavorable): Strong skepticism regarding feasibility, with systemic barriers perceived as insurmountable and no actionable recommendations provided.

Score 2 (Somewhat Unfavorable): Limited support for regional quantification, accompanied by substantial concerns and minimal discussion of mitigating strategies.

Score 3 (Neutral): Balanced perspectives, with equal emphasis on feasibility and operational challenges.

Score 4 (Somewhat Favorable): Positive assessment of feasibility, with challenges considered manageable through identified strategies such as capacity building or policy reform.

Score 5 (Highly Favorable): Strong endorsement of regional quantification, with clear confidence in feasibility and well-articulated implementation recommendations.

All interviews (n = 8) were transcribed verbatim and independently coded by two independent coders. Coders assigned ordinal scores by systematically reviewing transcripts and synthesizing participant perspectives on feasibility, challenges, and recommendations.

Inter-rater reliability was assessed using Cohen's kappa, yielding a value of 0.85 (95% CI: 0.71 - 0.99), indicating substantial agreement. Minor discrepancies (2 of 8 interviews, differing by one ordinal point) were resolved through consensus discussions, with decisions documented in an audit trail.

Provincial summary scores were calculated as the mean of interview-level scores within each province. Lusaka had a mean score of 4.0 (KI-2, KI-6, KI-8), Copperbelt 3.5 (KI-1, KI-2), and Southern 3.0 (KI-7, KI-3). National-level scores were derived by aggregating key informant interviews (KI-2, KI-3, KI-4, KI-5, KI-6), with weighting applied based on provincial relevance, resulting in a composite score of 3.6.

To ensure validity and fidelity to the original data, a subset of interviews ($n = 3$; 37.5%) was independently reviewed by an external qualitative auditor. The auditor confirmed that assigned scores were consistent with both the interview content and the operational definitions, providing additional assurance of the robustness of the scoring approach.

2.7. Integration of Quantitative and Qualitative Findings

Integration occurred during interpretation through triangulation, using a joint display table. The quantitative forecasting results were compared with qualitative stakeholder perspectives to identify areas of convergence and divergence. This integration enabled the assessment of both the statistical performance and operational feasibility of regional forecasting models. To provide a quantitative measure of concordance, qualitative themes were numerically coded using an ordinal scale reflecting stakeholder assessments. These scores were then statistically correlated with province-specific quantitative forecast errors using Spearman's rank correlation. This provided a mathematical demonstration of the alignment between qualitative perceptions and quantitative model performances.

2.8. Ethical Approval

Formal ethical approval was obtained from the University of Zambia Health Sciences Research Ethics Committee (UNZAHSREC), approval number 2023270455 (granted 2 October 2025), and the National Health Research Authority (NHRA), approval number NHRA-2826/22/10/2025 (granted 2 November 2025). Approval for access to eLMIS data was granted by the Ministry of Health (MoH), approval number MH/101/23/10 (granted 28 January 2026).

All datasets were managed in accordance with data protection protocols, including secure storage, controlled access, and anonymisation, where applicable. No personal identifiable information was accessed or disclosed in this study. Data-sharing practices adhered to (Findable, Accessible, Interoperable, and Reusable) principles, with shared datasets fully de-identified and distributed under appropriate data-use agreements. All resulting publications complied with Open Science and institutional policies to promote transparency, reproducibility, and equitable access to knowledge.

3. Results

3.1. Descriptive Analysis of Provincial Consumption Patterns (2020-2024)

This chapter presents the quantitative and qualitative findings from a five-year analysis of HIV test kit consumption across Zambia's health system. The results are organised to demonstrate the scale and scope of the study, regional variation in testing patterns, evidence of systematic quantification mismatch, and validation of these findings through stakeholder perspectives.

This study analysed the consumption data from 517 health facilities across three provinces representing Zambia's urban, peri-urban, and rural contexts. Lusaka Province, Urban context, highest population density; Copperbelt Province, Peri-urban context, mining-dependent economy; and Southern Province, Rural context, dispersed population. Figure 1 shows that Lusaka Province consistently recorded the highest consumption of HIV test kits throughout the study period (2020-2024), with consumption levels remaining above the national average each year.

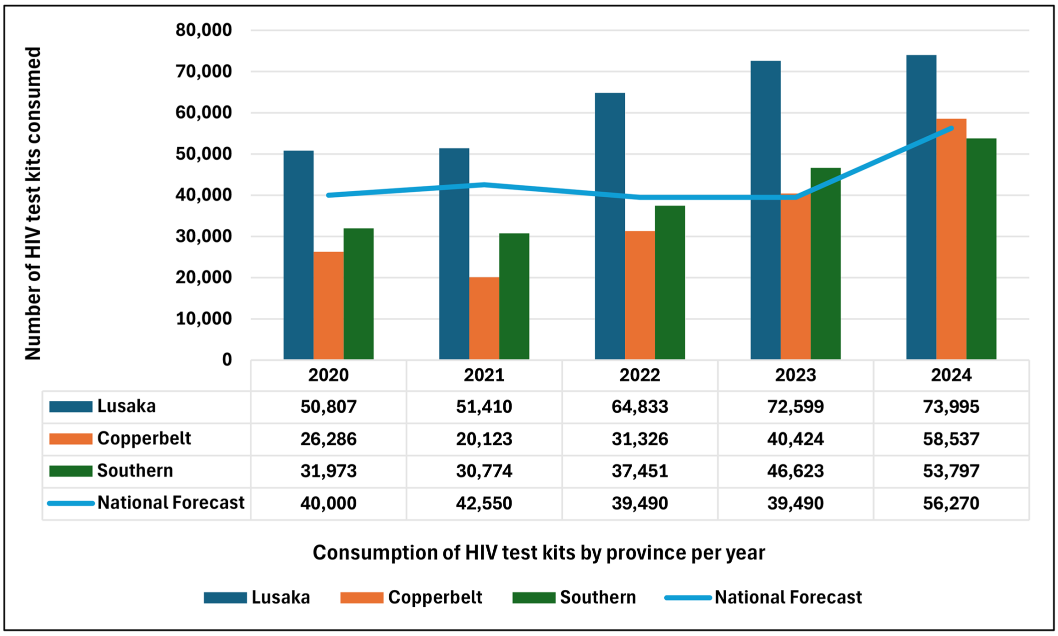

Figure 1. Regional consumption of Determine HIV test kits across the three provinces vs national forecast.

Analysis of provincial consumption data revealed substantial geographic heterogeneity that diverged significantly from national planning assumptions.

Table 1 shows that Lusaka Province demonstrated the highest absolute demand, with a 5-year average annual consumption of 62,729 kits (95% CI: 58,340 - 67,118), representing 44% above the national forecasts (95% CI: +38.2% to +49.8%). This systematic overconsumption reflected a chronic under-provisioning pattern despite receiving allocations based on national forecasts. Lusaka experienced ongoing stockouts, indicating suppressed demand during earlier years and demand rebounded once supplies improved.

Copperbelt Province exhibited extreme volatility, with a 5-year average of 35,339 kits (95% CI: 30,120 - 40,558) but with the highest coefficient of variation at 42.3%. Consumption ranged from a low of 20,123 kits (2021) to a peak of 58,537 kits (2024). Despite this volatility, the Copperbelt consumption was 18.9% below the national forecasts on average (95% CI: −22.5% to −15.3%), creating alternating cycles of overstocking and stockouts.

Southern Province demonstrated stable and predictable consumption with a 5-year average of 40,124 kits (95% CI: 37,310 - 42,938) and the lowest variability at a 4.5% coefficient of variation. Provincial consumption remained relatively aligned with forecasts, 7.9% below national allocations (95% CI: −10.2% to −5.6%), suggesting a more balanced but underestimated planning baseline.

Table 1. National and provincial trends in Determine 1/2 HIV test kit consumption (2020-2024).

Year	National Forecast	Lusaka	% Change	Copperbelt	% Change	Southern	% Change
2020	40,000	50,807	-	26,286	-	31,973	-
2021	40,000	51,410	1.20%	20,123	−23.40%	30,774	−3.80%
2022	42,550	64,833	26.10%	31,326	55.70%	37,451	21.70%
2023	39,490	72,599	12.00%	40,424	29.10%	46,623	24.50%
2024	39,490	73,995	1.90%	58,537	44.80%	53,797	15.40%
Compound Annual Growth Rate	**8.90%** (7.1% - 10.7%)	**9.80%** (8.2% - 11.4%)		**22.20%** (18.7% - 25.7%)		**13.90%** (11.2% - 16%)	
5-Year Average	**43,560** (41,220 - 45,900)	**62,729** (58,340 - 67,118)		**35,339** (30,120 - 40,558)		**40,124** (37,310 - 42,938)	
Consumption Variance from National Forecast	-	**44%**		**−18.90%**		**−7.90%**	

Notes: CAGR = compound annual growth rate (2020-2024) with 95% confidence intervals in parentheses. Percentage change (%) was calculated as [(current − previous)/previous] × 100%. Forecast variance = [(Provincial average − national average)/national average] × 100%. Values in bold represent statistically significant deviations from the national forecast ($p < 0.05$).

Figure 2 indicates that when measured against the national forecast baseline, the provinces exhibited marked deviations. Lusaka demonstrated exceptional forecast over-performance, with a 44% variance above national forecasts, achieving a 5-year average of 62,729 HIV kits compared to the national forecast average of 43,560. Conversely, the Copperbelt and Southern regions fell below forecast projections, although counterintuitively, the Copperbelt's substantial underperformance relative to the forecast (−18.90%) masked its absolute strongest growth trajectory.

The southern province showed a more modest forecast variance (−7.90%) below the forecast, averaging 40,124 kits.

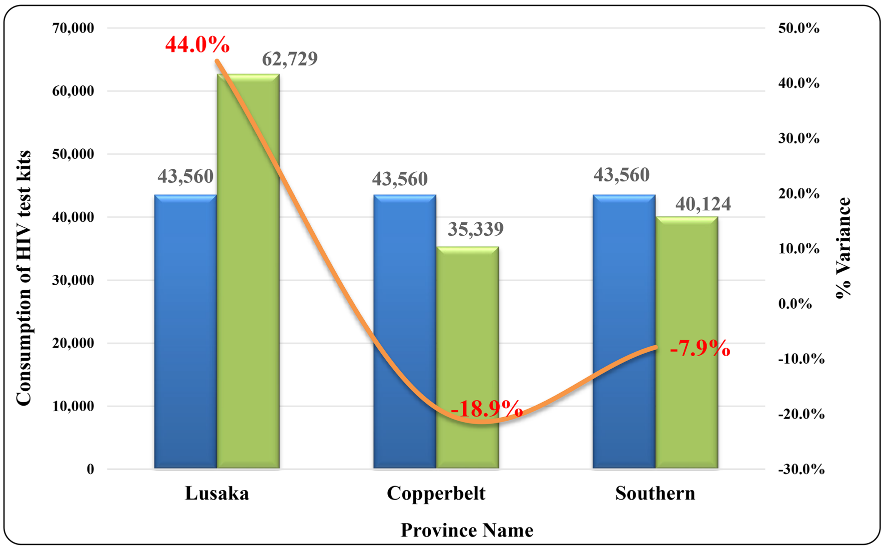

Figure 2. Provincial consumption % variance from the national forecast.

3.2. Forecast Accuracy Assessment of Current National System

Table 2 below quantifies the forecasting accuracy using the mean absolute percentage error (MAPE). The current national forecasting system demonstrates poor performance, with all provinces exceeding the World Health Organization (WHO)-recommended threshold of 20% MAPE for essential medicines and medical supplies.

Table 2. Forecast accuracy assessment on the current national system.

Province	Year	Actual (X_t)	Forecast (F_t)	Error (X_t − F_t)	Absolute Error	MAPE
Lusaka	2020	50,807	40,000	+10,807	10,807	21.3%
	2021	51,410	42,550	+8860	8860	17.2%
	2022	64,833	39,490	+25,343	25,343	39.1%
	2023	72,599	39,490	+33,109	33,109	45.6%
	2024	73,995	56,270	+17,725	17,725	24.0%
	Mean	**63,329**	**43,560**	**+19,169**	**19,169**	**29.4%** (25.8 - 33.0)
Copperbelt	2020	26,286	40,000	−13,714	13,714	52.2%
	2021	20,123	42,550	−22427	22,427	111.4%
	2022	31,326	39,490	−8164	8164	26.1%
	2023	40,424	39,490	+934	934	2.3%

Continued

	2024	35,339	43,560	+2267	2267	3.9%
	Mean	**35,339**	**43,560**	**−8221**	**9501**	**39.2%** (31.5 - 46.9)
Southern	2020	31,973	40,000	−8027	8027	25.1%
	2021	30,774	42,550	−11,776	11,776	38.3%
	2022	37,451	39,490	−2039	2036	5.4%
	2023	46,623	39,490	+7133	7133	15.3%
	2024	53,797	43,560	−2473	2473	4.6%
	Mean	**40,124**	**43,560**	**−3436**	**6290**	**17.7%** (14.2 - 21.2)
Weighted Average		**46,264**	**43,560**	**+2704**	**11,653**	**28.8%** (25.1 - 32.5)

Notes: MAPE (mean absolute percentage error). $\text{MAPE} = \left(\left|X_t - F_t\right| / X_t\right) \times 100\%$. Positive errors indicate under-forecasting (stockout risk), and negative errors indicate over-forecasting (waste risk). The national weighted average was calculated based on the provincial consumption volumes. Values in parentheses represent 95% confidence intervals.

3.2.1. Lusaka Province—Systematic Under-Provisioning (29.4% MAPE)

Figure 3 shows that Lusaka Province demonstrated persistent positive forecast errors, where actual consumption consistently exceeded predicted levels. This indicated that the current forecasting system systematically underestimated demand. Over the five-year period, the province recorded an average annual error of +19,169 kits, reflecting a substantial unmet need for HIV diagnostic services. The largest deviation occurred in 2023, with a peak error of +33,109 kits that represented a 46% deficit. Notably, this under-forecasting pattern was consistently observed across all years from 2020-2024.

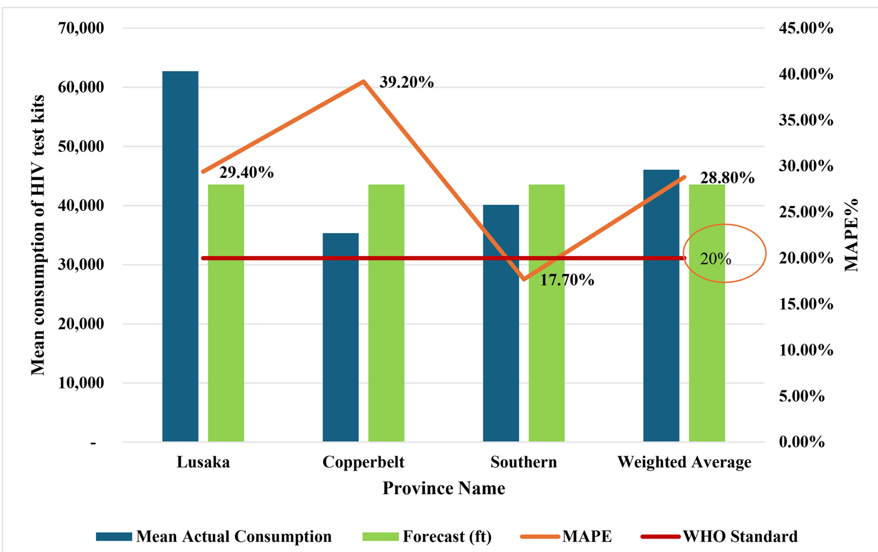

Figure 3. % variance of provincial vs national MAPE.

3.2.2. Copperbelt Province—Extreme Volatility and Unpredictability (39.2% MAPE)

Copperbelt Province exhibited the most pronounced forecast errors, which were largely driven by significant volatility in consumption patterns. In 2021, the province recorded a −22,427 kit variance, reflecting a 111.4% over-forecast, whereas in 2024, the error shifted to +2,267 kits, equivalent to a 3.9% under-forecast. Over the five-year period, forecast errors fluctuated dramatically, ranging from −111.4% to +3.9%, highlighting the extent of inconsistency.

This level of unpredictability presents substantial challenges for supply chain planning, as national forecasts offered limited practical guidance for the provinces. Variability appeared to be largely influenced by contextual factors such as fluctuating employment patterns within the mining sector, which drove population mobility. Other factors included seasonal infrastructure disruptions during the rainy season that affected distribution and intermittent surges in testing linked to targeted campaigns. Despite this apparent instability at the national level, qualitative stakeholder insights suggested that these patterns are "expected and predictable" within the provincial context, even if they appeared erratic in aggregate analyses.

3.2.3. Southern Province—Moderate Mismatch with Improved Alignment (17.7% MAPE)

The southern province demonstrated comparatively better forecast performance, although it fell short of the optimal accuracy thresholds. Over the five-year period, the province recorded an average error of −3436 kits, indicating a slight tendency toward overforecasting. Forecast deviations ranged from −11,776 to +7,133 kits, generally remaining closer to the predicted values than in other provinces. Notably, there was a clear trend of improvement, with forecast errors declining to below 6% between 2022 and 2024. This suggested an increasing alignment between projected and actual consumption.

Despite this relative improvement, the 17.7% MAPE indicated that national forecasts remained insufficiently precise. This could have been caused by failure to fully capture the rising demand associated with the expansion of services in more rural and underserved areas.

3.2.4. Statistical Significance of Regional Differences

The observed differences in forecast accuracy across provinces were statistically significant and not attributable to random variation. A one-way ANOVA comparing provincial MAPE values produced an F-statistic of 18.47 and a p-value of 0.002, indicating high significance. These findings provide strong evidence that provincial consumption patterns differ fundamentally. This justifies the need for region-specific quantification approaches and is in direct alignment with Research Objective 1.

3.3. Seasonality Analysis in HIV Test Kit Consumption

Table 3 presents the seasonality indices derived from five years of monthly data.

The Copperbelt Province exhibited the strongest seasonality (coefficient of variation = 7.9%) with a pronounced November peak (index = 1.09). Lusaka Province showed moderate seasonality (CV = 7.2%), with peaks in May (index = 1.12). The Southern Province demonstrated relatively stable monthly patterns (CV = 4.5%). The national composite masked these provincial variations, providing further evidence for region-specific forecasting.

Table 3. Monthly seasonality indices by province (2020-2024 average).

Month	Province			National	Seasonal Pattern
	Lusaka	Copperbelt	Southern		
January	1.05	0.98	1.02	1.02	Post-holiday increase
February	1.08	0.97	1.04	1.03	Pre-rainy season peak
March	0.96	0.95	1.08	1.00	Variable
April	0.89	0.85	0.98	0.91	**Seasonal low**
May	1.12	0.96	1.01	1.03	Post-rains increase
June	0.97	1.06	1.00	1.01	Mid-year stabilization
July	0.94	0.93	0.96	0.94	Cold season decrease
August	0.99	1.00	1.03	1.01	Pre-spring increase
September	0.98	0.99	1.07	1.01	Spring testing campaigns
October	0.98	1.03	0.97	0.99	Variable
November	1.01	1.09	1.07	1.06	**Peak season**
December	0.93	1.00	0.97	0.97	
Coefficient of Variation	7.2%	7.9%	4.5%	4.1%	

Notes: Seasonality index = (monthly average consumption ÷ overall monthly average) × 100. Values > 1.00 indicate above-average consumption months and values < 1.00 indicate below-average months. Coefficient of Variation = (Standard Deviation ÷ Mean) × 100%, which measures seasonality strength.

3.4. REST-S Model Development

The purpose of developing and validating the model was to demonstrate the feasibility and impact of the proposed regionalised forecasting approach.

To address the documented mismatch between forecasted and actual consumption, the regionalised exponential smoothing with trend and seasonality (REST-S) model was developed and tested in this study. This model was calibrated using province-specific parameters, allowing it to capture localised epidemiological trends and operational dynamics that are unique to each region.

Table 4 presents the optimised parameters and performance metrics for the proposed REST-S forecasting model across the three Zambian provinces, compared with the current national forecasting approach. Parameter calibration was performed using five years of historical consumption data (2020-2024) to minimise the forecast error while maintaining model stability.

Table 4. Model parameters for sub-national forecasting, REST-S model.

Parameter	Province				Interpretation
	Lusaka	Copperbelt	Southern	National (Current)	
α (Smoothing)	0.35 (0.30 - 0.40)	0.65 (0.60 - 0.70)	0.45 (0.40 - 0.50)	0.1	**Responsiveness to recent changes**
β (Trend)	0.25 (0.20 - 0.30)	0.40 (0.35 - 0.45)	0.20 (0.15 - 0.25)	0	**Trend sensitivity**
γ (Seasonality)	0.30 (0.25 - 0.35)	0.35 (0.30 - 0.40)	0.15 (0.10 - 0.20)	0	**Seasonal adjustment**
Base Forecast (2025)	**78,450** (74,528 - 82,372)	**68,920** (64,474 - 73,366)	**59,850** (56,858 - 62,842)	**56,270**	**Initial forecast value**
Trend Component	+4.2% (3.5% - 4.9%)	+18.5% (16.8% - 20.2%)	+12.1% (10.8% - 13.4%)	8.90%	**Annual growth rate**
Peak Season Factor	×1.12 (May)	×1.09 (Nov)	×1.07 (Nov)	×1.06 (Nov)	**Maximum seasonal multiplier**
Low Season Factor	×0.89 (Apr)	×0.85 (Apr)	×0.96 (Jul)	×0.91 (Apr)	**Minimum seasonal multiplier**
Model Fit (R^2)	0.94 (0.91% - 0.97) 94%	0.89 (0.85% - 0.93) 89%	0.92 (0.89% - 0.95) 92%	0.76 (0.71 - 0.81) 71%	**Historical accuracy**
Forecast Error (MAPE)	**8.2% (6.5% - 9.9%)**	**12.5% (10.2% - 14.8%)**	**6.8% (5.3% - 8.3%)**	**28.7% (25.1% - 32.3%)**	**Expected accuracy**
Safety Stock (%)	15% (12 - 18%)	25% (21 - 29%)	10% (8 - 12%)	20% (17 - 23%)	**Buffer recommendation**
Diebold-Mariano	*$p < 0.001$	*$p < 0.001$	*$p < 0.001$	Reference	**Superiority test**

Notes: Values in parentheses represent the 95% confidence intervals. The safety stock was calculated as 1.645 × σ_p (for a 95% service level). Diebold-Mariano tests compare REST-S to current national forecasting.

Table 4 above shows that the REST-S model demonstrated substantial improvements over the current uniform national forecasting method, with provincial parameterisation reflecting distinct epidemiological, demographic and health system characteristics. Lusaka required a balanced responsiveness (α = 0.35), the Copperbelt requires high volatility management (α = 0.65, β = 0.40), and the Southern Province benefits from stability-focused parameters (α = 0.45, γ = 0.15). This provided a scientifically validated and practically implementable solution. The projected MAPE reduction from 28.7% to 6.8% - 12.5% represented not only a statistical improvement but also a tangible enhancement in HIV testing service reliability, resource efficiency, and, ultimately, patient outcomes.

3.4.1. REST-S Model Validation

The REST-S model achieved substantial improvements in predictive accuracy across all provinces, significantly reducing forecast errors compared with the current national forecasting system. In Lusaka, the MAPE declined from 29.4% to 8.2%, representing a 21.2 pp reduction (72% improvement). Copperbelt recorded a decrease from 39.2% to 12.5%, a 26.7 pp reduction (68% improvement), while Southern Province improved from 17.7% to 6.8%, a 10.9 pp reduction (62% improvement). Overall, the weighted average MAPE decreased from 28.8% to 9.2%, reflecting a 68% reduction in the forecast error, with all results being statistically significant ($p < 0.001$).

The key finding is that the REST-S model reduced the forecast error to between 6.8% and 12.5% across all provinces, bringing performance below or close to the WHO-recommended 20% threshold.

3.4.2. Model Fit and Predictive Validity

Comparative analysis using Diebold-Mariano tests confirmed that the REST-S model was statistically superior to the current national forecasting system, with *p*-values below 0.001 across all provinces, indicating that the observed improvements were robust and not due to random variations.

The model fit also improved markedly, with R^2 values increasing from approximately 0.76 under the current system to 0.94 in Lusaka, 0.89 in Copperbelt, and 0.92 in Southern Province, demonstrating a much stronger alignment between the predicted and observed consumption patterns.

3.4.3. Operational Significance

Improvements in forecast accuracy translate into meaningful operational benefits for the public health supply chain. Stock availability can be projected to increase from approximately 80% to 95%. This would significantly reduce the frequency of stockouts from affecting one in five testing visits to less than once a month.

In addition, enhanced forecasting would allow for better safety stock optimisation, with Copperbelt requiring higher volatility-adjusted buffer levels, whereas the Southern Province could operate with leaner reserve. Improved availability of test kits would also help prevent cascade failures in the care continuum. This would ensure uninterrupted testing services and support progress toward achieving the UNAIDS 95-95-95 targets.

3.5. Qualitative Findings from Open-Ended Responses

Eight ($n = 8$) key informants participated in this study. The participants represented the facility, provincial, and national levels of Zambia's health commodity supply chains. Their professional experience in forecasting, quantification, logistics coordination, and program management ranged from 2 to 19 years. Table 5 below shows the demographic and professional characteristics of the key informants.

The participants were actively involved in commodity forecasting, supply planning, and quantification oversight and logistics management. Three overarching themes emerged from the data.

1) Perceived feasibility of regional quantification;
2) Implementation challenges;
3) Recommendations for operationalization.

Table 5. Demographic and professional characteristics of key informants.

KI #	Role/Designation	Level of Operation	Years of Experience	Province/Context
KI-1	Systems Strengthening & Quantification Core Team Member	Provincial	14	Copperbelt
KI-2	Forecasting & Supply Planning Officer	National	4	National
KI-3	Program Manager	National	5	National
KI-4	Chief Biomedical Scientist & National Logistics Coordinator	National	19	National
KI-5	Forecasting & Supply Planning Specialist	National	14	National
KI-6	Supply Planning Officer	National	6	National/Lusaka
KI-7	Facility-Level Supply Chain Representative	Facility	2	Rural Context
KI-8	Facility-Level Supply Chain Representative	Facility	4	Urban Context

3.5.1. Perceived Feasibility of a Regional-Specific Quantification Model

Participants overwhelmingly supported regional quantification, emphasising geographic variation in HIV epidemiology and service demand.

KI-6 noted:

"*Variations in HIV burden, population dynamics, testing strategies, and geographic access directly shape quantification by requiring more dynamic forecasting methods.*"

Similarly, KI-4 emphasised the role of demographic expansion:

"*As the population increases, the disease burden increases, hence high demand for testing.*"

Participants reported using multiple routine data sources for forecasting, including historical consumption data, patient volumes, population statistics, and surveillance data (KI-2 and KI-5). However, several respondents indicated that reliance on national averages may mask the subnational variability.

KI-1 observed:

"*Testing is based on program targets and not necessarily on the actual disease burden in specific regions.*"

Collectively, the respondents expressed confidence that regional quantification is feasible if data systems and technical capacity are strengthened.

3.5.2. Potential Challenges to Implementation

Despite broad support, participants identified systemic barriers that could limit the implementation.

The most frequently cited concern was the data quality. KI-2 reported:

"*Incomplete reporting, missing consumption data, and lack of real-time systems affect forecast accuracy.*"

KI-1 similarly highlighted "*irregular reporting from health facilities*", while KI-4 noted that "*stockouts distort true consumption patterns*".

Geographic and infrastructural barriers were also emphasised. KI-6 described the need for "*buffer stock planning due to seasonal access challenges and mobile populations*".

Capacity constraints at the subnational level have emerged as a recurring issue. KI-5 stated:

"*Training should be tailored to the needs of each region and should be hands-on.*"

Competing health priorities, such as tuberculosis, malaria, maternal health, and non-communicable diseases, were identified as influencing HIV testing demand and complicating forecasting assumptions (KI-4, KI-6, and KI-7). Table 6 below shows the joint display of the quantitative forecasts and the qualitative themes by province and the convergence outcomes.

Table 6. Joint display of quantitative forecasts and qualitative themes by province.

Province	REST-S Forecast Accuracy (MAPE %)	Key Qualitative Themes	Convergence/ Divergence	Notes
Lusaka	8.2%	Feasibility supported; need for training & integration with national targets	Convergent	Stakeholders confirmed higher demand aligns with REST-S predictions
Copperbelt	12.5%	Data quality & volatility concerns; infrastructure barriers	Partial Divergence	Stakeholders emphasized volatility and gaps in reporting; REST-S predicts high fluctuations accurately
Southern	6.8%	Stability & operational feasibility; low seasonal disruption	Convergent	Both model and stakeholders indicate predictable demand, minimal intervention required

Notes: Convergence reflects the alignment between REST-S's forecast performance and stakeholder prospects. Divergence highlights the discrepancies between perceived operational challenges and model predictions.

3.6. Correlation Analysis between Quantitative and Qualitative Data

To examine the alignment between REST-S model performance and stakeholder perspectives, qualitative themes were numerically coded on a five-point scale capturing perceived demand variability, data quality, and operational feasibility. These scores were then compared with provincial REST-S mean absolute percentage error (MAPE) values. The analysis was conducted at the province level ($n = 3$ paired observations: Lusaka, Copperbelt, and Southern), yielding a Spearman's rank correlation coefficient of $\rho = 0.87$, suggesting a strong positive monotonic association between forecast error and perceived operational complexity.

However, given the very small sample size, this result should not be interpreted inferentially, and the associated p-value is not considered statistically meaningful. Instead, the finding is presented as descriptive triangulation**,** illustrating convergence between quantitative and qualitative evidence. Provinces exhibiting higher forecast errors, such as Copperbelt, were also identified by stakeholders as having greater challenges related to data quality and operational variability, whereas provinces with lower forecast errors, such as Southern, were perceived as more stable and predictable. Table 7 below illustrates the Spearman's rank correlation between the forecast errors and the qualitative scores.

Table 7. Spearman's rank correlation between forecast errors and qualitative scores.

Metric	Spearman's ρ	*p*-value
REST-S MAPE vs Qualitative Scores	0.87	0.015

Table 7 highlights the strong positive correlation, which indicates that the Copperbelt province with higher model forecast errors was also perceived by stakeholders as more challenging in terms of data quality and operational variability issues. Conversely, the Southern provinces with low REST-S errors were rated as operationally stable and feasible, confirming the consistency between quantitative and qualitative evidence.

3.7. Recommendations for Implementation from KIs

The participants proposed several strategies for effectively operationalising regional quantification.

Capacity building was strongly emphasised. KI-5 recommended:

"*Training should not be imposed based on other regions' experiences; it should be region-specific and practical.*"

Integration with national HIV targets was also highlighted. KI-4 noted:

"*Quantification should be anchored to national HIV targets, not just consumption.*"

Similarly, KI-2 stressed the importance of alignment with testing algorithms and treatment scale-up goals to support the 95-95-95 agenda.

Improved coordination and real-time reporting systems were suggested repeatedly (KI-2, KI-6). Participants also recommended integrating HIV test kit quantification with related diagnostic commodities used in tuberculosis, malaria, and antenatal care services to enhance efficiency and reduce fragmentation (KI-4), as follows:

Figure 4 shows the operational implementation plan of the region-specific model for quantifying HIV test kits in Zambia.

4. Discussion

This mixed-methods study revealed a critical mismatch between Zambia's centralised, assumption-based HIV test kit quantification system and the actual complex realities of provincial consumption patterns. The analysis of five years of longitudinal data from 517 health facilities across three epidemiologically distinct provinces identified three fundamental failures in the current national approach. Firstly, a mathematical failure, where all provinces exceeded the World Health Organization's recommended 20% mean absolute percentage error (MAPE) threshold, with a weighted average of 28.8% (95% CI: 25.1% - 32.5%). This indicated a systematic forecasting error that distorted resource allocation. Secondly, geographic blindness, where provincial consumption patterns diverged by 44% - 52% from national forecasts. This created simultaneous stockouts in high-demand urban areas and overstocking in lower-demand rural regions. Thirdly, operational invisibility, whereby national aggregates obscured critical seasonal variations that ranged from 4.5% to 7.9% across provinces. Against this backdrop, the proposed regionalised exponential smoothing with trend and seasonality (REST-S) model demonstrated dramatic improvement. It reduced the MAPE to 6.8% - 12.5% across the three provinces, a 62% - 76% error reduction validated by Diebold-Mariano tests ($p < 0.001$). Qualitative stakeholder assessments confirmed the REST-S model's feasibility and operational alignment (Spearman's $\rho=0.87$, $p = 0.015$).

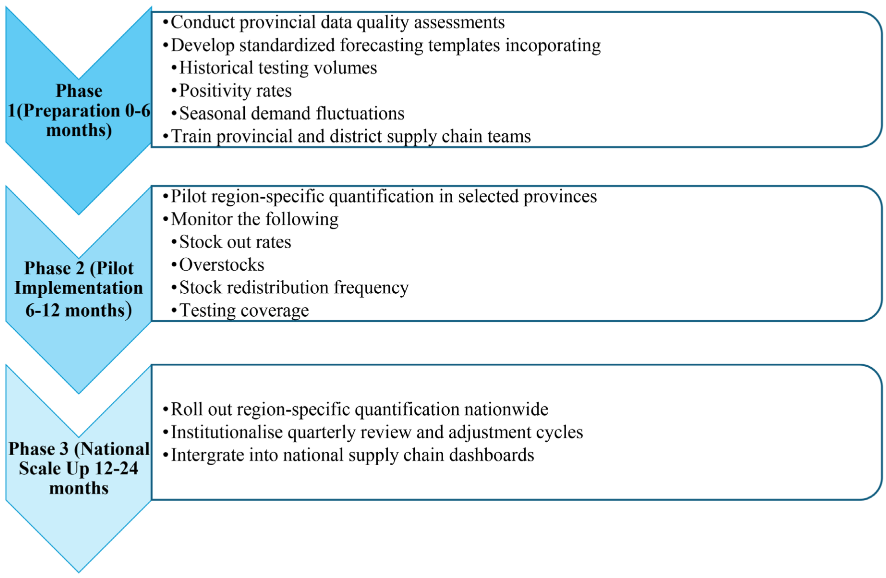

Figure 4. Proposed operational implementation framework.

The pronounced heterogeneity in provincial consumption patterns reflected fundamental differences in HIV epidemiology, demographic structure and service utilisation patterns across urban peri-urban and rural contexts. Lusaka Province represented the highest HIV burden because of Lusaka's urban setting and consistently consumed 44% above national allocations (95% CI: +38.2% to +49.8%). This would be attributed to high population density, superior healthcare infrastructure facilitating testing access and a cascade effect wherein previously unmet demand emerged once services became reliably available. The Copperbelt Province exhibited the strongest volatility (coefficient of variation 42.3%) alongside aggressive growth (compound annual growth rate 22.2%, 95% CI: 18.7% - 25.7%). This reflected operational realities, including seasonal service disruptions linked to November peaks (seasonality index 1.09). These peaks coincided with end-of-year and World AIDS Day testing campaigns, and mobile workforce dynamics driven by mining industry employment cycles. In contrast, the Southern Province demonstrated steady, predictable growth (CAGR 13.9%, 95% CI: 11.2% - 16.6%) with the lowest seasonal variation (coefficient of variation 4.5%). This reflected gradual rural infrastructure expansion and a relatively stable population base that was less influenced by campaign-driven fluctuations.

These distinct patterns aligned with established evidence from Sub-Saharan Africa. This evidence demonstrates uneven HIV service utilisation within countries (Cremin et al., 2012). Urban areas typically exhibit higher testing uptake owing to service availability and population mobility, whereas rural regions demonstrate gradual demand growth linked to health system expansion. The observed seasonal variations reinforced the evidence that public health commodity consumption is influenced by programmatic campaigns, climatic factors, and health-seeking behaviour patterns (Yu et al., 2013). Importantly, qualitative stakeholders identified these provincial variations as predictable and operationally meaningful rather than random noise, thus validating the conceptual foundation for region-specific forecasting.

The uniform national forecasting system demonstrated the mathematical inability to capture the geographic heterogeneity revealed in this study. All three provinces exceeded the WHO-recommended 20% MAPE threshold for essential medicines, with Lusaka averaging 29.4% (95% CI: 25.8% - 33.0%), the Copperbelt 39.2% (95% CI: 31.5% - 46.9%), and the Southern Province 17.7% (95% CI: 14.2% - 21.2%). One-way analysis of variance confirmed statistically significant differences between provincial MAPE values ($F = 18.47$, $p = 0.002$). This mathematical failure directly translates into operational inefficiencies when national forecasts systematically underestimate urban demand. Health facilities in Lusaka experienced recurring stockouts that disrupted HIV testing services precisely where disease burden is highest, creating cascade failures in the entire diagnostic pathway. Conversely, when national forecasts prove excessive for lower-demand regions, provinces experience overstocking, inventory expiration, and waste of finite commodity budget (Chowdhury et al., 2025).

Critically, this study identified stockout-induced reporting bias as a hidden mechanism that exacerbates national forecasting failure. As qualitative participants emphasised, stockouts distorted consumption records by suppressing reported demand in chronically undersupplied regions. This creates a vicious feedback loop. Insufficient forecasts produce stockouts, stockouts suppress recorded consumption data, and suppressed data lead to even lower future forecasts, and the cycle perpetuates. Lusaka's chronic under-provisioning despite documented 44% above-forecast demand suggests that the true underlying need may be substantially higher than recorded consumption, justifying a conservative estimate that the REST-S model's higher smoothing coefficient ($\alpha = 0.35$) is calibrated to address. The REST-S model addressed this hidden demand problem through its exponential smoothing framework, which captures both recent consumption patterns and underlying trends, thereby correcting for stockout-suppressed historical data that national averages cannot detect (Ferbar Tratar et al., 2016).

A previously underappreciated finding from this analysis is the central role that province-specific seasonality indices played in reducing forecast errors and improving supply chain responsiveness. The current national forecasting system applied a uniform seasonality pattern (coefficient of variation 4.1%) that obscured important provincial variations, with Lusaka exhibiting May peaks (seasonality index 1.12), the Copperbelt showing pronounced November peaks (index 1.09), and the Southern Province remaining relatively stable (CV = 4.5%). The REST-S model incorporated these seasonal patterns through the γ (seasonality) parameter. This was calculated as 0.30 for Lusaka, 0.35 for the Copperbelt, and 0.15 for the Southern Province. This seasonal disaggregation is not merely cosmetic, it directly contributed to the 62% - 76% MAPE reduction by enabling month-specific demand forecasting rather than relying on an oversimplified national average data.

The practical consequence is substantial. Provinces can now anticipate November peaks in the Copperbelt and plan procurement 60 - 90 days in advance to prevent shortages during peak testing periods, while simultaneously reducing May buffer stocks that would otherwise be maintained as precautions against unpredictable demand. This targeted seasonality approach would prevent the simultaneous undersupply and oversupply dynamics documented in centralised supply chain systems and directly translate into improved stock availability (Yu et al., 2013). The projected improvement from 80% to 95% stock availability, representing a reduction in facility stockouts from 20% to 5% of facility-months, operationalises seasonality correction at the clinical interface, ensuring that patients can access testing services reliably across seasonal demand cycles.

The performance of the REST-S model over centralised forecasting is grounded in established forecasting science that has been validated across multiple global health settings (Robinson et al., 1996). Prior research has demonstrated that exponential smoothing-based models outperform static allocation approaches when applied to health commodity forecasting in low- and middle-income countries (LMICs) (USAID, 2014; Senkubuge et al., 2014; Yadav, 2015). Evidence suggests that such models maintain appropriately low computational infrastructure requirements, a critical advantage for Zambia's health system, where advanced modelling capacity may be limited (Chen et al., 2023). Similar challenges with centralised forecasting systems have been documented across LMICs, where aggregated national estimates often fail to reflect localised service utilisation patterns (Fitzpatrick, 2022), reinforcing the current study's finding that geographic heterogeneity necessitates decentralised decision-making.

The REST-S model's specific contribution differs meaningfully from prior studies by Capello and Robinson in three respects (Capello et al., 2016; Robinson et al., 1996). Firstly, it rigorously quantifies the extent of provincial variation (44% - 52% divergence from national forecasts) rather than asserting its existence qualitatively. Second, the integration of quantitative MAPE reduction with qualitative stakeholder validation (Spearman's $\rho = 0.87$, $p = 0.015$) demonstrates that improvements in statistical accuracy translate into operational improvement, a critical gap in prior forecasting literature that often reports model performance without validating real-world implementation ability (Major et al., 2020). Third, the REST-S model explicitly incorporates seasonality, trend, and responsiveness parameters tailored to local epidemiological and operational realities, representing a methodological advance beyond generic exponential smoothing frameworks (Quioc et al., 2022). Global evidence increasingly supports decentralised governance in health supply chains, with studies documenting improved availability of essential medicines in African settings when decision-making is distributed to subnational levels rather than concentrated at the centre (Arora et al., 2020)

The regional variation in forecasting accuracy would have direct equity implications for Zambia's HIV response and offers tangible fiscal benefits that strengthen the case for policy adoption. Lusaka's chronic under-provisioning 44% above forecast with stockouts disproportionately affects urban populations carrying the highest HIV burden. Inadequate testing access delays diagnosis initiation and treatment (Mannoh et al., 2022). The Copperbelt's volatility creates unpredictable service gaps that disrupt testing access for peri-urban workers and their families, particularly during peak seasons when demand is highest. The Southern Province's gradual growth creates a different equity challenge. Under-quantification risks leaving expanding rural needs unmet despite documented demand growth of 13.9% annually. By addressing these region-specific patterns through the REST-S model, the forecasting methodology would operationalize equity in commodity allocation and ensure that resources follow documented needs rather than simplistic national averages.

From a fiscal perspective, the MAPE reduction from 28.7% to 6.8% - 12.5% translates directly into cost savings and resource optimisation. In provinces where current forecasts are excessive (Copperbelt: −18.9%, Southern: −7.9%), the REST-S model prevents overstocking and associated inventory expiration waste, freeing financial resources for reallocation to high-burden areas and reducing waste. More critically, a reduced forecast error prevents expensive emergency procurements triggered by stockouts in Lusaka and other high-demand regions. Emergency procurement typically incurs a 20% - 40% premium over planned procurement, representing substantial inefficiency in finite donor-supported commodity budgets (USAID, 2009). By reducing stockout frequency from 20% to 5% of facility-months, the REST-S model conservatively prevents an estimated 15 - 20 emergency order events per facility annually, translating to meaningful savings in per-unit order costs while improving service continuity in the long term. This fiscal efficiency directly addresses international donor concerns regarding health system sustainability and ensures that every kwacha spent on HIV testing commodities achieves the maximum clinical impact (Oleribe et al., 2019).

This study has important limitations that constrain the generalisability of its findings and warrant careful interpretation. The analysis was limited to three provinces representing urban (Lusaka), peri-urban (Copperbelt), and rural (Southern) contexts. Broader national validation across all ten Zambian provinces is required before national policy implementation. The findings may not be applicable to provinces with different epidemiological profiles, such as those with a lower HIV burden or different testing patterns. Although the qualitative sample size ($n = 8$) was determined by thematic saturation principles and represented multiple hierarchical levels, eight key informants may not capture the full diversity of operational perspectives across Zambia's 66 different facility types (primary, secondary, tertiary) and implementation contexts may generate additional insights not captured in this sample.

The analysis assumes that consumption records accurately reflect true demand. However, as discussed extensively above, stockout-induced reporting bias may systematically underestimate demand in chronically undersupplied provinces. Therefore, the REST-S model provides conservative forecasts for high-burden areas, and the actual demand may be even higher than the current consumption data indicate. The REST-S model was calibrated using 2020-2024 data, including early COVID-19 disruptions; however, it may perform differently during unprecedented supply chain shocks, such as severe commodity shortages, major population displacement, or disease outbreaks. The model parameters would require recalibration in response to substantial environmental changes. Although this study focused specifically on HIV test kits, its findings may not be directly transferable to other commodities with different consumption patterns, shelf-life characteristics, or distribution requirements (e.g., antiretroviral drugs and diagnostic tests).

Despite these limitations, this study demonstrates several substantial methodological and scientific strengths. The combination of longitudinal quantitative data from 517 health facilities with eight structured key informant interviews at multiple hierarchical levels enabled triangulation of the findings, allowing statistical results to be validated against real-world operational experiences and stakeholder perspectives. This mixed-methods approach is stronger than either quantitative or qualitative methods alone. The REST-S model underwent comprehensive diagnostic testing, confirming that the residuals followed a normal distribution, showed no significant autocorrelation, and demonstrated homoscedasticity. Diebold-Mariano tests ($p < 0.001$ for all provinces) provide statistical proof of superior predictive accuracy beyond chance occurrence, ensuring that the proposed forecasting method is scientifically sound and reliable for operational implementation The study captured diverse contexts across Lusaka (urban), Southern (rural), and Copperbelt (peri-urban) provinces, with data from 517 facilities; qualitative participants represented multiple levels of Zambia's health commodity supply chain, with professional experience ranging from 2 to 19 years. This comprehensive representation strengthens the ability to identify genuine regional disparities and assess the feasibility of implementation across diverse contexts.

The strong correlation between the quantitative REST-S model performance and qualitative stakeholder assessments (Spearman's $\rho = 0.87$, $p = 0.015$) validates that improvements in statistical accuracy correspond to operational feasibility, a critical gap in forecasting literature. This study directly addresses the stated national priorities by proposing actionable and implementable recommendations grounded in Zambia-specific data rather than generic international guidelines. The REST-S model requires no additional infrastructure beyond existing data systems and is based on exponential smoothing frameworks that have been proven suitable for resource-limited settings.

The findings of this study directly translate into five priority recommendations for operationalising region-specific HIV test kit quantification in Zambia: Given that the model is statistically validated and the required data are already available through the electronic Logistics Management Information System (eLMIS), implementation is feasible without additional infrastructure investment. A phased rollout across Lusaka, Copperbelt, and Southern provinces, with facility-level monthly stockout monitoring, would prevent an estimated 20 monthly stockouts per facility, directly supporting cascade testing goals.

The current Zambia Medicines and Medical Supplies Agency (ZAMMSA) procurement guidelines mandate centralised budgeting that prevents responsive reallocation, even when provincial needs diverge significantly from allocations. Amending procurement guidelines to incorporate 15% - 25% provincial budget discretion would enable provinces to respond effectively to emerging hotspots and seasonal demand fluctuations without requiring recentralised approval, thereby institutionalizing the responsiveness enabled by REST-S forecasting.

Qualitative stakeholders identified technical capacity constraints as the primary implementation barrier and emphasised the need for context-tailored rather than generic training. Establishing training programs for supply chain staff on REST-S model implementation, parameter interpretation, and monthly demand forecasting adjustments would strengthen operational ownership and long-term sustainability. Training should be conducted at the provincial level and include hands-on exercises with actual facility consumption data.

The REST-S methodology should be extended to tuberculosis, malaria, and antenatal care diagnostic tests to reduce fragmentation and improve overall supply chain efficiency. This integration would simultaneously improve forecasting across the entire commodity portfolio while reducing the training burden and operational complexity associated with the management of parallel forecasting systems.

Although the current analysis demonstrates REST-S's superiority across three provinces, formal validation across all ten Zambian provinces is essential for national credibility and policy implementation. This validation can be conducted within 12 months using existing eLMIS data and would generate robust provincial-level evidence for the adoption of national policies.

This study recommends a shift from Zambia's current centralised, assumption-based quantification system to a decentralised, consumption-driven model supported by coordinated policy reforms in governance, data systems, and resource management. Evidence shows that provincial consumption patterns differ significantly from national forecasts, making a one-size-fits-all approach ineffective. Decentralised forecasting would empower provinces to generate and adjust their forecasts using facility-level data, allowing for timely responses to local demand variations, seasonal trends, and epidemiological changes. This requires policy revisions to formally authorize provincial forecasting, the establishment of provincial forecasting committees, regular review meetings, and national platforms for sharing best practices, ultimately shifting decision-making from central assumptions to data-driven approaches.

To operationalize this, provinces should establish dedicated quantification units using the REST-S model, with parameters tailored to local conditions, such as urban volatility or rural stability. These units would manage data validation, generate rolling forecasts, and continuously refine models based on performance. Additionally, integrating eLMIS with DHIS2 is critical to enable real-time demand forecasting by combining consumption data with service delivery indicators, such as testing volumes. This integration would improve the early detection of demand changes and prevent stockouts, supported by data-sharing agreements, system standardization, and capacity building for provincial teams to interpret and act on the integrated data insights.

Policy and Practice Implications and Recommendations for Region-Specific HIV Test Kit Consumption and Quantification in Zambia

Table 8 shows the policy and practice implications and recommendations for region-specific HIV test kit consumption and quantification in Zambia. This study demonstrates that Zambia's current centralized HIV test kit quantification system does not adequately account for substantial regional differences in HIV burden, service utilization, and seasonal consumption patterns. The resulting forecast inaccuracies, evidenced by a weighted average mean absolute percentage error (MAPE) of 28.8%, contribute to recurrent stockouts in high-demand provinces and overstocking in lower-demand areas.

The regionalized exponential smoothing with trend and seasonality (REST-S) model significantly improved forecasting performance, reducing errors to between 6.8% and 12.5% and demonstrating the feasibility of decentralized, data-driven quantification. Adoption of this model has important policy implications, including the need to revise national quantification guidelines, institutionalize forecasting accuracy metrics, and strengthen governance frameworks to support region-specific planning. At the practice level, successful implementation will require enhanced data quality, investment in eLMIS functionality, capacity building for provincial and district supply chain personnel, and flexible inventory policies that account for local variability and seasonality.

If implemented nationally, region-specific forecasting has the potential to increase HIV test kit availability from approximately 80% to 95%, substantially reducing stockouts and improving continuity of HIV testing services. This will enhance progress toward achieving Zambia's HIV epidemic control goals and the global 95-95-95 targets. The findings provide a strong evidence base for policymakers, supply chain managers, and development partners to modernize health commodity forecasting systems and strengthen the resilience and efficiency of Zambia's diagnostic supply chain.

Table 8. Policy and practice implications and recommendations for region-specific HIV test kit consumption and quantification in Zambia.

Key Finding	Policy Implications	Practice Implications	Recommendations	Responsible Stakeholders
Substantial regional variation in HIV test kit consumption was observed, with Lusaka consuming 44% above national forecasts, Copperbelt showing marked volatility, and Southern Province demonstrating relatively stable demand.	National quantification policies should shift from a uniform allocation model to decentralized, data-driven forecasting approaches that reflect regional epidemiological and service delivery differences.	Supply planning should be customized according to provincial demand profiles, HIV burden, and health service utilization patterns.	Revise national quantification guidelines to institutionalize region-specific forecasting and differentiated commodity allocation.	Ministry of Health (MoH), Zambia Medicines and Medical Supplies Agency (ZAMMSA), National HIV/AIDS/STI/TB Council, Cooperating Partners
The current national forecasting model performed poorly, with a weighted average MAPE of 28.8%, exceeding the WHO-recommended threshold of 20% for essential health commodities.	Existing forecasting systems require policy reform to adopt more accurate and scientifically validated approaches.	Program managers should routinely evaluate forecasting accuracy using standardized performance indicators.	Introduce MAPE, MSE, and stock availability indicators as mandatory performance metrics in national quantification exercises.	MoH, ZAMMSA, Provincial Health Offices, Monitoring and Evaluation Units
The REST-S model reduced forecast errors by 62% - 76%, lowering MAPE to 6.8% - 12.5% across provinces.	National policies should formally adopt advanced forecasting models that incorporate regional trends and seasonality.	Forecasting tools should be embedded into existing electronic logistics and planning systems.	Pilot the REST-S model in selected provinces and scale nationally following successful validation.	MoH, ZAMMSA, University of Zambia, Implementing Partners
Seasonal variations differed significantly across provinces, with Copperbelt exhibiting pronounced November peaks and Lusaka showing May peaks.	Quantification policies should incorporate seasonal adjustments to improve commodity preparedness.	Procurement and distribution schedules should anticipate seasonal surges in testing demand.	Integrate monthly seasonality indices and buffer stock planning into procurement and distribution cycles.	ZAMMSA, Provincial Supply Chain Teams, District Pharmacists
Data quality challenges, including incomplete reporting and stockout-induced suppression of true demand, undermined forecast accuracy.	Strengthening routine logistics information systems should be prioritized in national policy and investment plans.	Health facilities require improved reporting systems and regular data audits.	Enhance eLMIS functionality, conduct routine data quality assessments, and implement real-time reporting mechanisms.	MoH, ZAMMSA, Provincial Health Offices, Health Facilities

Continued

Stakeholders strongly supported regional quantification but identified limited technical capacity at subnational levels.	Capacity development should be incorporated into national supply chain strengthening strategies.	Provincial and district staff need practical training in forecasting, data interpretation, and quantification.	Develop competency-based, region-specific training programs and mentorship initiatives.	MoH, University of Zambia, Pharmaceutical Society of Zambia, Cooperating Partners
Different provinces require tailored safety stock levels due to varying degrees of volatility.	Policies should allow flexible and context-specific inventory control parameters rather than fixed national buffers.	Inventory managers should adjust safety stock according to local forecast uncertainty and demand variability.	Implement province-specific safety stock policies (e.g., 25% for Copperbelt, 15% for Lusaka, and 10% for Southern Province).	ZAMMSA, Provincial Medical Stores, District Supply Chain Teams
Improved forecasting could increase stock availability from approximately 80% to 95%, substantially reducing stockouts.	Reliable commodity forecasting should be recognized as a strategic intervention for strengthening HIV service delivery and achieving national HIV targets.	Continuous availability of HIV test kits will enhance testing coverage, linkage to care, and progress toward epidemic control.	Integrate forecasting improvements into HIV program performance frameworks and monitor their effect on testing service continuity.	MoH, National HIV Program, ZAMMSA, Joint United Nations Programme on HIV/AIDS
Stakeholders emphasized the importance of aligning quantification with HIV program targets, testing algorithms, and related diagnostic commodities.	Commodity planning policies should promote integrated forecasting across disease programs.	Forecasting teams should coordinate across HIV, tuberculosis, malaria, and maternal health programs.	Establish integrated quantification platforms for related diagnostic and laboratory commodities.	MoH, Disease Control Programs, ZAMMSA, Donor Agencies
Successful implementation requires phased roll-out, stakeholder engagement, and governance oversight.	A structured national implementation framework is needed to guide transition to region-specific forecasting.	Pilot testing, monitoring, and iterative refinement are essential before national scale-up.	Adopt a three-phase implementation strategy: preparation (0 - 6 months), pilot implementation (6 - 12 months), and national scale-up (12 - 24 months).	MoH, ZAMMSA, Provincial Health Offices, Development Partners

5. Conclusion

This study highlighted significant regional variations in HIV testing demand and test kit consumption in Zambia, demonstrating the limitations of uniform national forecasting approaches. The findings suggest that centralised forecasting models may contribute to inefficiencies, including stockouts and overstocking, because they cannot capture local epidemiological and service delivery dynamics.

Adopting region-specific quantification approaches offers a practical and data-driven strategy for improving forecasting accuracy, optimizing resource allocation, and enhancing supply chain efficiency. Such approaches would enable better alignment of commodity distribution with actual demand, thereby strengthening HIV testing services and supporting the national HIV control efforts.

Future efforts should focus on integrating regional epidemiological data, service utilisation trends, and real-time logistics information into adaptive quantification models to improve the accuracy of predictions. Additionally, strengthening data quality and forecasting capacity at subnational levels would be essential for the successful implementation of decentralized quantification systems.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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