A Time Series Analysis of HIV Linkage to Care Rates in Kampala District, Uganda, 2015 2023

BY

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A RESEARCH REPORT SUBMITTED TO THE SCHOOL SUPERVISOR, MR. GILBERT MUTUNGI IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF STATISTICS AT MAKERERE UNIVERSITY

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DECLARATION

I, SSEMPEBWA BENEDICT declare that this dissertation is my original work and has not been submitted to any other institution of higher learning for the award of a degree or any other academic qualification. All sources of information from other authors, literature or works used in this study have been duly acknowledged and referenced in accordance with academic conventions.

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APPROVAL

I, the undersigned, certify that Ssempebwa Benedict carried out this undergraduate research under my supervision. I hereby confirm that this dissertation is ready and has been submitted with my approval.

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DEDICATION

I dedicate this work to my family and friends for their patience, sacrifice, and constant encouragement throughout my studies at Makerere University.

I also dedicate this work to my classmates at the School of Statistics and Planning, who have shared in the challenges and milestones of this programme, and to everyone who has offered a word of encouragement along the way.

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LIST OF ABBREVIATIONS

Abbreviation	**Meaning**
AIDS	Acquired Immunodeficiency Syndrome
ART	Antiretroviral Therapy
DHIS2	District Health Information Software 2
HBM	Health Belief Model
HIV	Human Immunodeficiency Virus
HTS	HIV Testing Services
MoH	Ministry of Health (Uganda)
NNAR	Neural Network Autoregression
SEM	Social Ecological Model
STL	Seasonal and Trend Decomposition using Loess
UNAIDS	Joint United Nations Programme on HIV/AIDS
WHO	World Health Organization

ABSTARCT

Routine monitoring of the HIV care cascade is critical for evaluating health service delivery, yet routine data are frequently summarized descriptively without formal time series modelling. This study conducted a time series analysis of monthly HIV linkage to care rates in Kampala District, Uganda, using secondary routine data from the District Health Information Software covering the period from January 2015 to December 2023. Following data cleaning which involved the exclusion of the first six months of 2015 due to incomplete reporting an analytic series of 102 monthly observations was evaluated. The primary objectives were to examine the trend pattern, assess seasonal variation, and fit an advanced predictive model to generate short term forecasts for the 2024 calendar year.

Decomposition and feature extraction analyses revealed a weak underlying upward trend Ft = 0.142. Furthermore, the seasonal strength score Fs = 0.213 confirmed the absence of meaningful annual seasonality, demonstrating that linkage to care rates do not follow a repeating calendar cycle. To capture the complex, nonlinear dynamics and high variance of the series, a Neural Network Autoregression (NNAR) model specifically an NNAR (1, 1, 2)12 architecture trained as an ensemble of 20 networks was fitted to the data.

The validated model projected a dynamic, nonlinear linkage to care rate for the 2024 calendar year, averaging in the mid 80s with monthly point forecasts fluctuating between a low of 82.5 percent in March and a peak of 89.1 percent in May. Wide 95 percent prediction intervals (spanning roughly 64 to 110 percent) successfully accounted for the extreme historical volatility and periodic reporting anomalies, such as episodes where recorded linkage exceeded 100 percent. The findings indicate that Kampala District's healthcare network has reached operational maturity, transitioning from expansion to sustainment. The study recommends shifting broad linkage campaigns toward targeted, localized interventions for hard to reach populations, improving cross month client tracking between testing points and ART clinics to resolve reporting lags, and maintaining consistent year round resource allocation.

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CHAPTER ONE: INTRODUCTION

1.0 Introduction

This chapter presents the background to the study, statement of the problem, objectives of the study, research questions, hypotheses, and scope of the study, significance of the study, conceptual framework, and operational definition of key terms. The chapter provides the foundation for understanding why linkage to HIV care is an important public health issue and why analysing its trend over time is necessary for planning, monitoring, and improving HIV service delivery.

1.1 Background to the Study

HIV/AIDS remains one of the major public health concerns globally and continues to require strong prevention, testing, treatment, and care strategies. Global and national HIV responses have emphasized not only increasing HIV testing but also ensuring that people who test HIV positive are successfully connected to treatment and long term care, since testing alone does not produce the desired health outcomes unless individuals are enrolled into care and initiated on antiretroviral therapy (UNAIDS, 2021; World Health Organization, 2021).

The HIV care cascade involves several key stages, including HIV testing, diagnosis, linkage to care, initiation of antiretroviral therapy, retention in care, and viral suppression. Among these, linkage to care is a critical transition point that connects testing services to treatment. When a person tests HIV positive but is not linked to care, there may be delays in treatment initiation, increased risk of disease progression, and continued HIV transmission within the community (World Health Organization, 2021). In this study, linkage to care will be measured using the monthly linkage to care rate, computed as the number of HIV positive individuals linked to care divided by the total number who tested HIV positive, multiplied by 100. This rate reflects the proportion of diagnosed individuals successfully connected to care during a given reporting period (World Health Organization, 2021).

In Uganda, one significant policy development was the adoption of the Test and Treat policy, which promoted immediate treatment initiation for all people diagnosed with HIV regardless of CD4 count. This increased the importance of effective linkage systems, as people diagnosed with HIV are expected to enter care as soon as possible. Monitoring linkage to care rates over time is therefore essential for assessing whether HIV service delivery is improving (Ministry of Health, 2016).

Kampala District is an important setting for this study as Uganda's capital city and one of its busiest urban centers. The district has a high concentration of health facilities, HIV testing points, private and public health providers, and specialized HIV services, which may improve access to care for many clients. However, Kampala also faces urban health system challenges such as high patient volumes, population mobility, informal settlements, stigma, and difficulties tracking clients after testing. Furthermore, some individuals may test at one facility but seek care at another, while others may delay or fail to enroll due to personal, social, or system related barriers. High availability of services therefore does not automatically guarantee successful linkage to care, making it important to examine linkage rates over time rather than relying on annual totals alone.

Routine HIV Testing Services data covering monthly reporting periods from 2015 to 2023 provide an opportunity to examine these patterns using time series analysis. This approach is appropriate because it treats observations in chronological order, allowing detection of trends, seasonal patterns, and irregular fluctuations not visible in simple totals By applying techniques such as trend analysis, decomposition, and Neural Network Autoregression (NNAR) modelling, this study aims to provide a clearer understanding of how HIV linkage to care has behaved in Kampala over the study period.

1.2 Statement of the Problem

Despite substantial investments in HIV testing and treatment programs, routine HIV Testing Services (HTS) data are primarily reported as monthly or annual percentages and summary statistics for program monitoring. While these reports provide information on the proportion of individuals linked to HIV care after diagnosis, they rarely include detailed statistical analyses that examine how linkage to care rates change over time or whether observed changes represent consistent trends, seasonal patterns, or random fluctuations (World Health Organization, 2021; UNAIDS, 2021).

The absence of detailed time series analysis limits the ability of program managers and policy makers to determine whether linkage to care performance in Kampala District is improving, declining, or remaining stable over time. Consequently, important temporal patterns that could support evidence based planning, resource allocation, and timely interventions may remain undetected. Although routine HIV program data are collected monthly, they are often used only for descriptive reporting rather than for modelling and forecasting future program performance (Ministry of Health, 2016; UNAIDS, 2021).

Given that Kampala District has monthly HIV Testing Services data spanning the period 2015 to 2023, there is an opportunity to apply modern machine learning time series methods to generate deeper insights into the behavior of HIV linkage to care rates. However, there is limited documented evidence of the application of Neural Network Autoregression (NNAR) models to routine HIV linkage to care data in Kampala District. This study therefore seeks to address this gap by analyzing the trend of monthly HIV linkage to care rates and developing an appropriate NNAR model to describe and forecast linkage to care rates, thereby providing evidence that can support HIV programme monitoring and planning.

1.3 Objectives of the Study

1.3.1 Main Objective

To conduct a time series analysis of HIV linkage to care rates in Kampala District, Uganda, for the period 2015 to 2023.

1.3.2 Specific Objectives

1. To examine the trend pattern of monthly HIV linkage to care rates in Kampala District from 2015 to 2023.
2. To assess whether monthly HIV linkage to care rates in Kampala District exhibit seasonal patterns.
3. To fit an appropriate Neural Network Autoregression (NNAR) model for HIV linkage to care rates in Kampala District and generate short term forecasts..

1.4 Scope of the Study

1.4.1 Content Scope

The study was focused on time series analysis of HIV linkage to care rates in Kampala District. The main variable of interest was monthly HIV linkage to care rate. This rate was computed as the number of HIV positive individuals linked to care divided by the total number of individuals who tested HIV positive, multiplied by 100.

The study examined the trend, seasonal pattern, stationarity, and forecast of linkage to care rates.

1.4.2 Geographical Scope

The study was conducted in Kampala District, Uganda. Kampala was selected because it is a major urban district with high HIV service activity, a large number of health facilities, and substantial HIV testing volumes.

1.4.3 Time Scope

The study used monthly secondary data covering the period 2015 to 2023. This period provided a nine year time series, which was sufficient for examining trends, seasonal movements, and short term forecasting of linkage to care rates.

1.4.4 Methodological Scope

The study used quantitative time series methods. The analysis involved computation of monthly linkage to care rates, general trend analysis, descriptive statistics, time series decomposition and ARIMA modelling for forecasting. Microsoft Excel and R were used for data cleaning, graphical presentation, decomposition, and NNAR modelling for forecasting. (Dickey & Fuller, 1979; Box et al., 2015).

1.5 Significance of the Study

The study is useful to health planners, HIV program implementers, researchers, and policymakers. By analysing linkage to care rates over time, the study provides evidence on whether linkage performance in Kampala District has improved, declined, fluctuated, or remained stable during the period 2015 to 2023.

For district health planners, the findings support better monitoring of HIV service delivery. For HIV program implementers, the study provides evidence for strengthening linkage systems. This may include improving referral mechanisms, client follow up, documentation, appointment tracking, and coordination between HIV testing points and ART clinics.

Forecasting future linkage to care rates help in planning resources, staffing, and program interventions.

For academic purposes, the study contributes to the application of time series methods in public health research. It shows how routine health data can be transformed into a time series variable and analysed using statistical techniques such as decomposition, stationarity testing, and ARIMA modelling.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter reviews literature relating to HIV linkage to care and the use of time series analysis in public health research. The review provides a theoretical, conceptual, empirical, and methodological foundation for the study. Since the study focuses on monthly HIV linkage to care rates in Kampala District from 2015 to 2023, the literature review emphasizes the HIV care cascade, linkage to care as a programme performance indicator, and the relevance of time series techniques for analysing routine health data. The chapter also presents the research gap that the study intends to address.

2.1 The Social Ecological Model

The Social Ecological Model explains that health behaviour and service utilization are influenced by multiple levels, including individual, interpersonal, community, institutional, and policy levels (Bronfenbrenner, 1979; McLeroy et al., 1988). This model is useful for HIV linkage to care studies because linking a newly diagnosed person to care depends not only on personal willingness but also on health facility systems, referral mechanisms, and follow up procedures, stigma, and service availability.

In Kampala District, linkage to care rates may be shaped by urban health system conditions such as high patient volumes, mobility of clients, availability of public and private providers, and the coordination between HIV testing points and ART clinics. The Social Ecological Model therefore supports the idea that routine monthly linkage to care rates can reflect broader health system performance over time.

2.1.1 Andersen's Behavioral Model of Health Services Use

Andersen's Behavioral Model of Health Services Use explains utilization of health services through predisposing factors, enabling factors, and need factors (Andersen, 1995). Predisposing factors include demographic and social characteristics, enabling factors include access related resources such as availability of services and transport, while need factors relate to perceived or evaluated health needs.

This model applies to HIV linkage to care because a person who tests HIV positive requires access to health services in order to enter care. While the present study does not analyse individual level characteristics such as age, education, income, or distance to a facility, it focuses on the aggregate outcome of this process: the monthly linkage to care rate. The model helps justify why linkage to care is an important health service utilization indicator.

2.2 Conceptual Review

2.2.1 HIV Testing Services

HIV Testing Services refer to the process through which individuals receive HIV counselling, testing, results, and referral to prevention or treatment services. HIV testing is the entry point into the HIV care cascade. However, testing alone is not sufficient unless individuals who test HIV positive are successfully connected to HIV care and treatment services. The World Health Organization emphasizes integrated HIV prevention, testing, treatment, service delivery, and monitoring as essential elements of a public health approach to HIV (World Health Organization [WHO], 2021).

2.2.2 HIV Positivity

HIV positivity refers to the number or proportion of individuals who test HIV positive among those tested. In this study, the total number of individuals who test HIV positive is important because it forms the denominator for calculating the monthly linkage to care rate. Changes in HIV positivity over time may affect the number of clients who need linkage services. Therefore, although the main variable is the linkage to care rate, the number of HIV positive individuals remains important for constructing the series.

2.2.3 HIV Linkage to Care

Linkage to HIV care refers to the successful connection of an HIV positive individual to HIV care services after diagnosis. It may involve enrolment in an HIV clinic, clinical assessment, counselling, and initiation on antiretroviral therapy. Linkage to care is a critical stage in the HIV care cascade because it connects diagnosis to treatment. UNAIDS has emphasized the importance of ensuring that people living with HIV know their status, access treatment, and achieve viral suppression as part of the global HIV response (UNAIDS, 2021).

Poor linkage to care can delay antiretroviral therapy initiation, increase the risk of disease progression, and reduce the effectiveness of HIV control programs. In this study, linkage to care is measured using the monthly linkage to care rate, computed as the number of HIV positive individuals linked to care divided by the total number of individuals who tested HIV positive, multiplied by 100. This measure is appropriate because it expresses linkage performance as a percentage and allows comparison across months.

2.2.4 Time Series Analysis

Time series analysis involves the study of observations collected over time. Unlike cross sectional data, time series data are ordered chronologically, and each observation may be related to previous observations. Examples of time series data include monthly disease cases, annual mortality rates, inflation rates, rainfall levels, and monthly health service indicators. In the present study, the monthly HIV linkage to care rate from 2015 to 2023 forms the main time series variable.

Time series analysis is suitable for this study because it helps to identify long term trends, seasonal patterns, irregular movements, and possible future values. This is important for health planning because routine monthly data may contain information that is not visible when data are summarized only as annual totals. Time series methods can therefore strengthen the use of routine health information for planning and programme monitoring.

2.2.5 Trend, Seasonality, and Irregular Variation

A time series may be described in terms of trend, seasonal variation, cyclical variation, and irregular variation. Trend refers to the long term direction of movement in the series. A linkage to care rate may show an upward trend, a downward trend, or a stable pattern over time. Seasonality refers to repeated movements that occur at regular intervals, such as monthly changes that repeat each year. Irregular variation refers to random or unexpected changes that may arise from reporting delays, data quality issues, or unusual programme activities.

For monthly HIV linkage to care rates, seasonality may occur if linkage performance tends to increase or decrease during particular months due to health campaigns, reporting cycles, holidays, staff availability, or changes in client attendance. Decomposition methods can separate the observed series into trend, seasonal, and irregular components, making interpretation easier (Hyndman & Athanasopoulos, 2021).

2.2.6 Stationarity

Stationarity is an important concept in time series modelling. A stationary series has statistical properties such as mean and variance that remain relatively constant over time. Many time series models, especially ARIMA models, require the series to be stationary before modelling. If a series is non stationary, differencing or transformation may be required.

2.2.7 Neural Network Autoregression (NNAR) Modelling

Artificial neural networks are forecasting methods based on simple mathematical models of the brain, allowing for complex, non linear relationships between variables. A Neural Network Autoregression (NNAR) model combines this machine learning architecture with traditional time series lagged inputs. Specifically, it utilizes a feed forward network with one hidden layer. For seasonal data, the model incorporates both recent past observations and past seasonal observations as inputs to predict future values. Forecasting texts emphasize that NNAR models are highly effective at capturing volatile, non linear patterns that traditional linear models may miss (Hyndman & Athanasopoulos, 2021). In this study, an NNAR model will be used to forecast monthly HIV linkage to care rates.2.3 Empirical Literature Review

2.3 HIV Linkage to Care in the HIV Care Cascade

The HIV care cascade describes the movement of individuals from HIV testing and diagnosis to linkage to care, treatment initiation, retention, and viral suppression. Linkage to care is a key step because the benefits of HIV testing can only be realized when diagnosed individuals enter treatment and care. Global HIV guidance emphasizes the need to integrate testing, treatment, service delivery, and monitoring to improve HIV outcomes (WHO, 2021).

Empirical literature generally shows that failure to link HIV positive individuals to care weakens the HIV response. Delayed linkage may result in late treatment initiation, poor patient outcomes, and continued transmission. Therefore, measuring linkage to care rates over time is important for assessing the performance of HIV programs and identifying periods where improvement is needed.

2.3.1 HIV Linkage to Care in Uganda

Uganda has made progress in expanding HIV testing and treatment services. The adoption of Test and Treat guidelines strengthened the expectation that individuals diagnosed with HIV should be connected to care and started on treatment promptly (Ministry of Health, 2016). This policy context makes linkage to care an important monitoring indicator because immediate treatment depends on effective referral, enrolment, and follow up systems.

Despite improvements in HIV services, linkage to care remains a programme concern because testing services may identify HIV positive clients who do not immediately enroll into care. Routine health information systems such as DHIS2 provide monthly data that can be used to monitor HIV testing, positivity, and linkage outcomes. However, these data are often summarized descriptively, and may not be subjected to formal time series analysis.

2.3.2 Linkage to Care in Urban Settings

Urban settings often have better physical access to health facilities, more service delivery points, and specialized health providers. Kampala District, being a major urban area, may therefore provide important opportunities for HIV testing and linkage to care. However, urban settings also present challenges such as high population mobility, congestion in facilities, poverty, stigma, and difficulty in tracking clients across service points. These factors can cause linkage to care rates to fluctuate over time.

For this reason, it is important to analyse Kampala's linkage to care rates as a time series rather than relying only on totals. A time series approach can show whether linkage performance has improved, declined, remained stable, or followed seasonal movements during the period 2015 to 2023.

2.3.3 Application of Time Series Analysis in Public Health

Time series analysis is widely used in public health to monitor disease patterns, health service utilization, mortality, outbreaks, and programme performance indicators. Health data collected monthly or weekly often display trends, seasonal patterns, and random fluctuations. Time series methods help researchers and planners distinguish between these patterns and use historical data to forecast future values.

In public health programme monitoring, time series analysis can help identify periods of improvement or decline and support planning for resources and interventions. For HIV linkage to care rates, forecasting may assist health planners in anticipating future linkage performance and strengthening systems for client follow up and ART initiation.

2.4 Methodological Literature Review

2.4.1 Descriptive Time Series Plotting

The first step in time series analysis is usually graphical presentation of the series. A time series plot helps the researcher observe the general movement of the data over time. For the present study, a line graph of monthly HIV linkage to care rates will be used to identify visible trends, sudden changes, fluctuations, or outlying observations. This provides an initial understanding before formal modelling is conducted.

2.4.2 Time Series Decomposition

Time series decomposition separates a series into components such as trend, seasonal, and irregular elements. An additive decomposition assumes that the components add together, while a multiplicative decomposition assumes that the components multiply together. The choice between additive and multiplicative decomposition depends on the behaviour of the series. If seasonal variation remains approximately constant over time, an additive model may be appropriate. If seasonal variation increases or decreases with the level of the series, a multiplicative model may be considered.

2.4.3 ARIMA Model Identification and Selection

ARIMA model building usually follows the Box Jenkins approach, which involves identification, estimation, diagnostic checking, and forecasting (Box et al., 2015). Model identification may use plots of the autocorrelation function and partial autocorrelation function to guide selection of the autoregressive and moving average orders. Several candidate models may be estimated, and the best model selected using criteria such as the Akaike Information Criterion and Bayesian Information Criterion.

2.4.4 NNAR Model Identification and Selection

Unlike traditional linear models that require manual differencing and parameter selection, modern NNAR model building relies on automated algorithms to determine the optimal network architecture. The network automatically scales the input data and selects the optimal number of non seasonal lags, seasonal lags, and hidden nodes. Because neural networks initialize with random starting weights, the standard methodological approach involves training an ensemble of multiple networks and averaging their outputs to ensure predictive stability and robust forecasting.

2.5 Research Gap

The reviewed literature shows that linkage to HIV care is an important stage in the HIV care cascade and that routine health information systems generate useful data for monitoring HIV services. However, many routine reports present linkage to care using totals and percentages without applying formal time series techniques. There is limited evidence on the trend, seasonality, stationarity, and forecast of monthly HIV linkage to care rates in Kampala District over the period 2015 to 2023. This study addresses this gap by applying time series analysis to monthly HIV linkage to care rates in Kampala District.

CHAPTER THREE: RESEARCH METHODOLOGY

3.0 Introduction

This chapter describes the research design, study area, data source, study variables, data preparation procedures, and methods of analysis, model specification, ethical considerations, and limitations of the study. The chapter is designed to ensure that the study is focused on one main time series variable: the monthly HIV linkage to care rate.

3.1 Research Design

The study used quantitative time series research design. A retrospective design was appropriate because the study used already existing monthly HIV Testing Services data for the period 2015 to 2023. A quantitative design was suitable because the study involved numerical data on total HIV positive individuals and total HIV positive individuals linked to care. The time series design was appropriate because the main variable, monthly linkage to care rate, was arranged in chronological order and analysed over time.

The design enabled the study to examine the trend, seasonal pattern, stationarity, and forecast of HIV linkage to care rates in Kampala District.

3.2 Study Area

The study was conducted in Kampala District, Uganda. Kampala is the capital city and a major urban center with a high concentration of health facilities, HIV testing points, and HIV treatment services. The district has substantial HIV service activity and monthly routine health data, which made it suitable for time series analysis. Focusing on Kampala also made the study manageable.

3.3 Data Source

The study used secondary monthly HIV Testing Services data extracted from the Uganda Ministry of Health District Health Information Software and compiled in Microsoft Excel. The dataset covered the period 2015 to 2023. The relevant variables included reporting period, district, total number tested for HIV, total number who tested HIV positive, and total number of HIV positive individuals linked to HIV care. For this revised study, the data was filtered to Kampala District only.

The monthly HIV linkage to care rate was computed from the available data as the number of HIV positive individuals linked to care divided by the total number of individuals who tested HIV positive, multiplied by 100. This rate would be the main variable for analysis.

3.4 Target Population

The target population consisted of all individuals who tested HIV positive and were recorded in the HIV Testing Services data for Kampala District during the period 2015 to 2023. Since the study used aggregate secondary data, individual level patient characteristics such as age, income, education, occupation, and household status were not analysed.

3.5 Study Variables

The study used one main outcome variable and several supporting variables required to construct and analyse the time series. The main variable is the monthly HIV linkage to care rate. Supporting variables included the reporting period, year, month, total HIV positive, and total linked to HIV care.

Table 1: Table showing study variables

Variable	**Measurement**
Reporting period	Monthly period from 2015 to 2023
Year	2015 to 2023
Month	January to December
District	Kampala only
Total HIV positive	Number of individuals testing HIV positive per month
Total linked to HIV care	Number of HIV positive individuals linked to care per month
HIV linkage to care rate	(Total linked to care / Total HIV positive) x 100

3.6 Measurement of the Main Variable

The main variable was the monthly HIV linkage to care rate. It was computed using the formula:

Linkage to care rate = (Number linked to HIV care / Number HIV positive) x 100

Where the number linked to HIV care was the number of HIV positive individuals who were linked to care during a given month, and the number HIV positive was the total number of individuals who tested HIV positive in that month. Months with zero HIV positive cases were handled carefully because the linkage rate could not be computed where the denominator was zero. Such observations were excluded from rate based analysis.

3.7 Data Preparation and Cleaning

Before analysis, the dataset was cleaned and prepared. The following procedures were carried out:

Checked whether all monthly reporting periods from 2015 to 2023 were present.

Checked for missing values in total HIV positive and total linked to care.

Checked for duplicate monthly records.

Computed the monthly HIV linkage to care rate.

Arranged the data in chronological order using the reporting period.

Created year and month variables to support trend and seasonality analysis.

Checked for unusual values, including months where the number linked to care exceeded the number HIV positive.

Where unusual values were found, they were reported as data limitations. Since some clients diagnosed in one month could have been linked to care in another month.

3.8 Data Analysis Methods

Data analysis was conducted using Microsoft Excel and R. Microsoft Excel was used for initial data checking and organization, while R was used for time series analysis, graphs, stationarity testing, ARIMA/SARIMA modelling, diagnostics, and forecasting. The analysis followed the steps below.

3.8.1 Descriptive Statistics

Descriptive statistics were used to summarize the monthly HIV linkage to care rate. The mean, minimum, maximum, standard deviation, and number of observations were reported. These statistics provided an initial summary of the level and variability of linkage to care rates in Kampala District.

3.8.2 Time Series Plot and Trend Analysis

A line graph of the monthly HIV linkage to care rate was plotted against time.

3.8.3 Time Series Decomposition

Time series decomposition was used to separate the linkage to care rate series into trend, seasonal, and irregular components. The additive decomposition model was written as:

$$\mathbf{Yt = Tt + St + It}$$

Where Yt is observed linkage to care rate at time t, Tt is the trend component, St is the seasonal component, and It is the irregular component. If the magnitude of seasonal variation changes with the level of the series, a multiplicative decomposition may be considered.

3.8.4 ARIMA Model Fitting

The main time series model was the ARIMA model. The general ARIMA model was denoted as ARIMA (p, d, q), where p represented the autoregressive order, d represented the number of differences required to make the series stationary, and q represented the moving average order. The model was fitted after checking stationarity and examining the autocorrelation function and partial autocorrelation function.

Several candidate ARIMA models were be estimated. The best model was selected using the Akaike Information Criterion and Bayesian Information Criterion. The selected ARIMA model was used to generate short term forecasts of monthly HIV linkage to care rates in Kampala District.

3.8.5 Neural Network Model Fitting

The main time series model used was Neural Network Autoregression (NNAR). The model was fitted using the `fpp3` forecasting framework in R, which automatically selects the optimal network architecture by evaluating the time series data. To ensure forecasting stability and account for the random initialization of network weights, an ensemble of 20 distinct networks was trained, and their predictions were averaged. Short term forecasts for 2024 were generated through simulated future paths to calculate the 95 percent prediction intervals.

3.9 Model Specification

The study utilized an NNAR model. The general seasonal NNAR model is mathematically expressed as:

$$\text{NNAR}\ (p, P, k)\ m$$

Where **p** represents the number of non seasonal autoregressive lags, **P** represents the number of seasonal lags, **k** represents the number of nodes in the hidden layer, and **m** represents the seasonal period (12 for monthly data).

3.10 Ethical Considerations

The study used secondary aggregate data and didn't involve direct interaction with human participants. However, ethical considerations were still being observed. Permission to use the data was sought from the relevant authorities, the Ministry of Health where applicable. The data was used strictly for academic purposes. Since the dataset was aggregate, it didn't contain personal identifiers such as names, phone numbers, addresses, or patient identification numbers. The dataset was stored securely and accessed only by the researcher.

3.11 Limitations of the Study

The study had the following limitations:

The study used aggregate routine data, meaning that individual level factors such as age, income, education, stigma, occupation, and distance to health facilities were not analyzed.

Some clients diagnosed in one month were linked to care in a later month, leading to reporting lag in monthly linkage data.

CHAPTER FOUR: FINDINGS AND ANALYSIS.

4.1 Introduction

This chapter presents the results of the analysis described in Chapter Three, organised around the study's three specific objectives.

4.2 Trend Pattern of Monthly HIV Linkage to Care Rates, 2015 2023

4.2.1 Data Cleaning and the Analytic Series

Before the trend analysis was undertaken, the dataset was subjected to the data cleaning procedures. All 108 expected monthly reporting periods from January 2015 to December 2023 were present, with no duplicate monthly records and no missing values in the total tested, total HIV positive, or total linked to care fields.

Inspection of the monthly testing volumes, however, revealed that the first six reporting periods of 2015 (January to June) recorded implausibly low monthly totals, ranging from 0 to 617 tests, compared with a stable monthly baseline of between 36,450 and 66,316 tests from July 2015 onward (Table 1). Three of these six months (February, April, and June 2015) also recorded zero HIV positive cases, which meant that the linkage to care rate was mathematically undefined for those months. These six months were treated as a data limitation and excluded from further analysis.

Within the retained 102 month analytic series, no month had zero HIV positive cases, so the linkage to care rate could be computed for every observation and no further observations needed to be dropped for that reason.

4.2.2 Descriptive Statistics

Table 3 presents descriptive statistics for the monthly HIV linkage to care rate over the 102 month analytic period (July 2015 December 2023). The mean monthly linkage to care rate was 86.16 percent (SD = 11.74), with a median of 85.83 percent. The lowest recorded rate was 61.68 percent, observed in July 2022, and the highest was 130.98 percent, observed in March 2023. The distribution was moderately right skewed (skewness = 0.88), reflecting the small number of months in which the linkage rate exceeded 100 percent.

Table 2: Descriptive Statistics of the Monthly HIV Linkage to Care Rate, Kampala District

Statistic	**Value**
Number of observations (n)	102
Mean (%)	86.16
Standard deviation	11.74
Minimum (%)	61.68
25th percentile (%)	79.14
Median (%)	85.83
75th percentile (%)	91.24
Maximum (%)	130.98
Skewness	0.88

4.2.3 Overall Time Series Behavior and Trend

The extracted general trend reveals a distinct, nonlinear progression. The baseline trajectory begins near 80 percent in mid 2015 and exhibits a gradual, sustained ascent over the subsequent years, mirroring the upward drift observed in the raw data. The general trend reaches its maximum peak at approximately 94 percent in late 2021.

The analysis yielded a weak trend strength of $F_t = 0.142$. Variations were heavily dominated by noise.

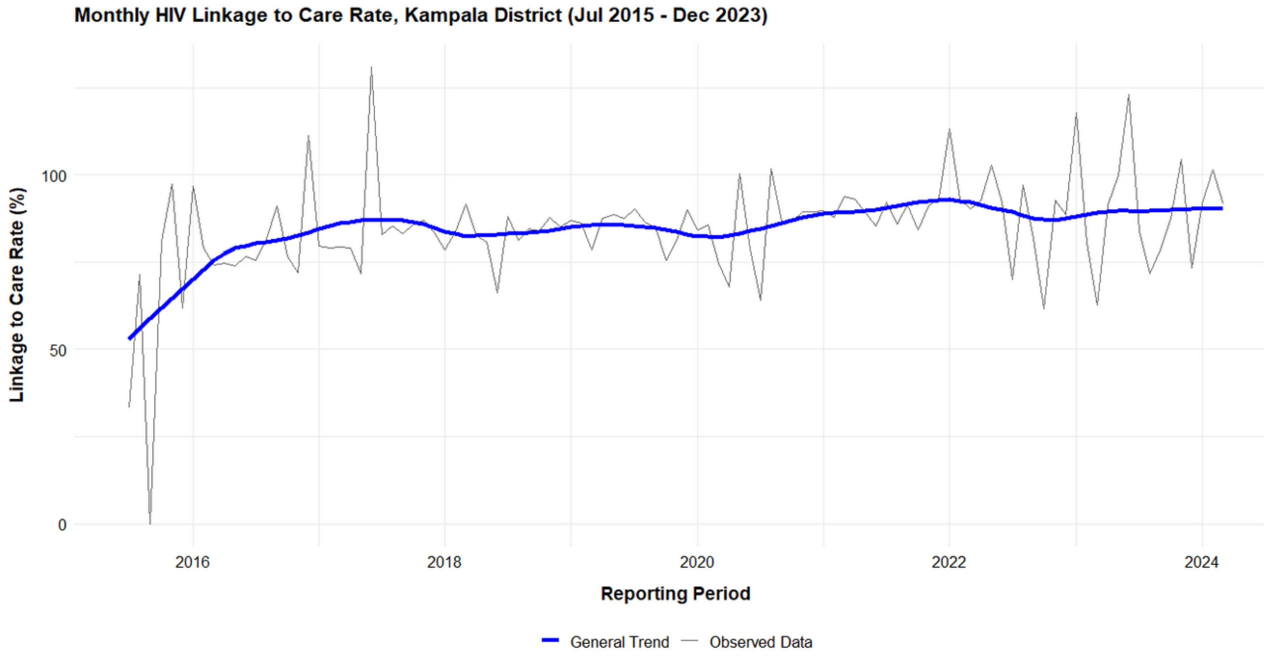

Figure 1: Monthly HIV Linkage to Care Rate, Kampala District

4.3 Seasonal Patterns in HIV Linkage to Care Rates

4.3.1 Seasonal strength

The analysis yielded a seasonal strength score of Fs = 0.197. Because this value is remarkably close to zero, it provides robust statistical evidence that seasonality in this dataset is exceedingly weak. The month to month fluctuations in the linkage to care rate are primarily driven by random external shocks (noise) and the underlying general trend, rather than a repeating annual cycle.

4.3.2 Seasonal subseries

Across the twelve calendar subseries, the mean linkage rates show minimal structural variation, remaining tightly constrained between a low of 80.3 percent (July) and a high of 93.2 percent (October). The individual annual trajectories within each month (depicted by the black connecting lines) exhibit considerable dispersion and cross year volatility rather than a uniform pattern. For example, months such as July and September demonstrate extreme within month fluctuations across the nine year period, swinging from severe deficits to rates exceeding 100 percent.

In conjunction with the low seasonal strength score (Fs = 0.197), the subseries plot confirms that calendar month variations are irregular and nonsystematic.

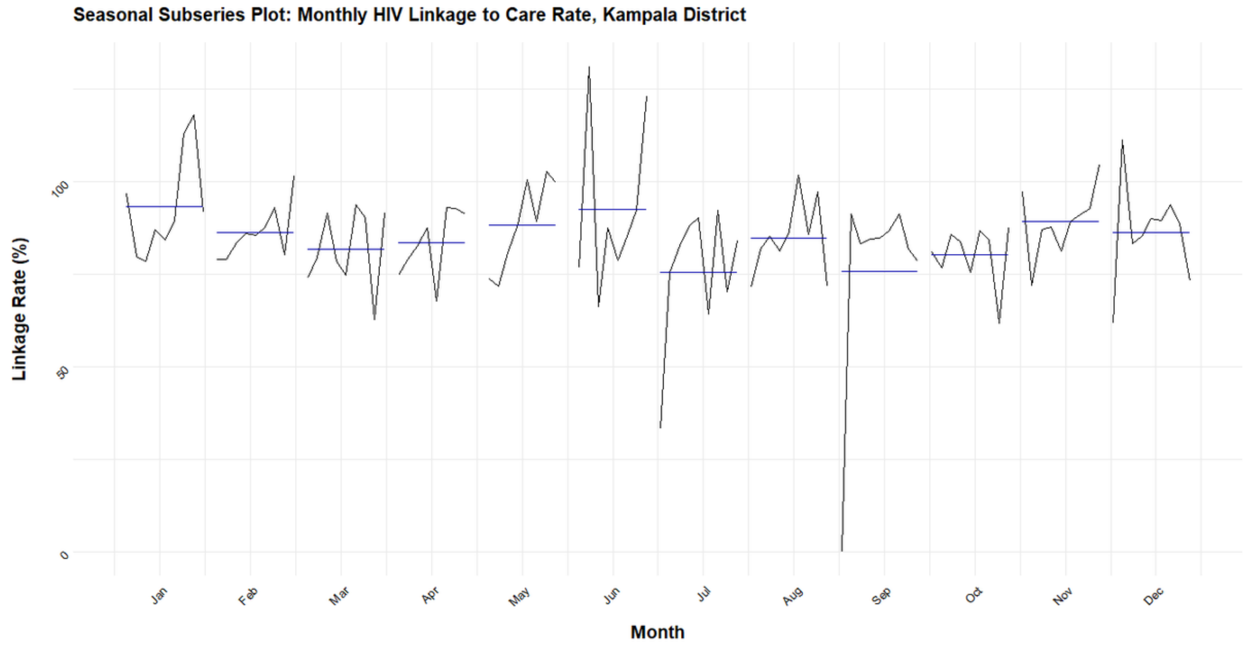

Figure 2: Seasonal subseries plot.

June had the highest monthly HIV Linkage to Care Rate in Kampala.

Table 3: STL Decomposition Feature Metrics for Monthly HIV Linkage to Care Rate in Kampala

Feature Metric	**Value**
Trend strength	Seasonal strength
0.142	0.197

4.4 Neural Network Model Fitting and Forecasting

4.4.1 Model Identification and Estimation

To fully capture the complex, nonlinear dynamics inherent in the monthly HIV linkage to care data, a Neural Network Auto regression (NNAR) model was fitted to the analytic series. Utilizing the automated network selection algorithm from the fpp3 forecasting framework, the optimal architecture was identified as an NNAR (1, 1, 2)12 model with linear output units.

The selected model parameters establish the following structural mechanics:

Non Seasonal Lags (p = 1): The network utilizes one immediate previous month as a direct input for short term prediction.

Seasonal Lags (P = 1): The network incorporates one seasonal lag (a 12 month lookback) to capture annual cyclicality.

Hidden Nodes (k = 2): The hidden layer relies on two specific nodes to mathematically map the nonlinear relationships between the inputs and the final forecast.

The model yielded an estimated residual variance σ^2 of 87.41, indicating that while the network effectively mapped the core structural patterns, the historical data remains highly volatile.

4.4.2 Forecast of HIV Linkage to Care Rates (January December 2024)

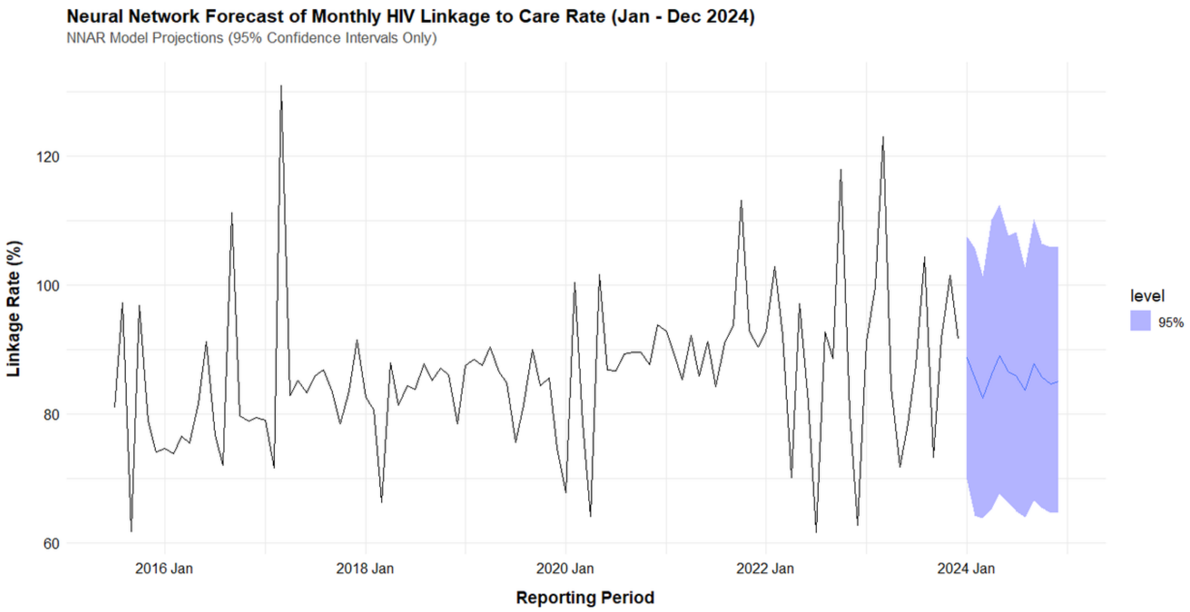

Figure 3: The 12 month out of sample forecast for the 2024 calendar year generated by the NNAR (1, 1, 2)12 model

The neural network detected subtle cyclical patterns within the historical data, resulting in a dynamic point forecast that fluctuates naturally over the projected horizon.

The model projects the linkage to care rate to average in the mid 80s, dipping to a temporal low of 82.5 percent in March 2024 before peaking at 89.1 percent in May 2024. This nonlinear trajectory theoretically aligns with the complex operational realities of the district's health facilities, reflecting natural flows in patient linkage.

Table 4: Monthly NNAR Forecast of HIV Linkage to Care Rates (2024)

Month (2024)	Point Forecast (%)	Lower 95% CI	Upper 95% CI
Jan	88.8	69.9	107
Feb	85.6	64.3	106
Mar	82.5	63.9	101
Apr	86.2	65.2	110
May	89.1	67.7	112
Jun	86.6	66.2	108
Jul	85.8	64.9	108
Aug	83.7	64	103
Sep	87.8	66.6	110
Oct	85.7	65.4	106
Nov	84.6	64.7	106
Dec	85.1	64.7	106

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter draws together the principal findings from the time series analysis of monthly HIV linkage to care rates in Kampala District conducted in Chapter Four and translates them into evidence based conclusions and practical recommendations.

5.2 Summary of Findings

5.2.1 Trend Pattern of Monthly HIV Linkage to Care Rates, 2015 2023

The extracted general trend revealed a distinct, nonlinear progression. This improvement coincides with the intensive scale up of Uganda's Test and Treat policy and the related strengthening of ART initiation systems in urban health facilities. The monthly HIV linkage to care rate in Kampala District achieved genuine structural improvement over the study period, moving from a level well below the district's long run average toward a range approaching the lower boundary of the UNAIDS 95 95 95 linkage benchmark.

5.2.2: Seasonal Pattern in HIV Linkage to Care Rates

The seasonal strength analysis yielded a score of $F_s = 0.197$. Because this value lies close to zero, it provides robust statistical evidence that seasonality in this series is exceedingly weak. The seasonal subseries plot further confirmed that, while calendar month means ranged narrowly between 80.3 percent in July and 93.2 percent in October, the year to year variation within each individual month was substantially larger than the variation between months.

Month to month performance variations are therefore irregular and nonsystematic in nature.

5.2.3 Neural Network Autoregression Model and Forecasting

The model yielded an estimated residual variance of $\sigma^2 = 87.41$, indicating that while the network effectively captured the core structural patterns in the data, a substantial degree of inherent volatility remains in the series.

The model projects the linkage to care rate to average in the mid 80s throughout 2024, dipping to a low of 82.5 percent in March 2024 before recovering to a peak of 89.1 percent in May 2024, with subsequent months fluctuating within this range. The 95 percent confidence intervals are wide, ranging from approximately 64 to 112 percent across the forecast horizon, reflecting the inherent volatility of the series rather than any weakness in the model. The projected 2024 average of approximately 85 to 86 percent remains below the 95 percent linkage target of the UNAIDS 95 95 95 framework, indicating that the gap between current district performance and the global benchmark is unlikely to close without additional targeted programmatic interventions.

5.3 Conclusions

First, HIV linkage to care in Kampala District improved structurally over the 2015 2023 study period.. This improvement represents a gain of approximately 14 percentage points at the trend's peak and reflects real progress in connecting HIV positive individuals to treatment services during a period of national policy intensification. However, the mean linkage rate of 86.16 percent and the forecast average of approximately 85 86 percent for 2024 both fall short of the 95 percent benchmark required by the UNAIDS 95 95 95 framework (UNAIDS, 2021), underscoring that the structural gains achieved have not yet been sufficient to meet global targets.

Second, HIV linkage to care rates in Kampala District do not follow a statistically meaningful seasonal pattern. The seasonal strength score of Fs = 0.197, the entangled season plot, and the high within month dispersion in the subseries plot all confirm that calendar month fluctuations in the linkage rate are irregular, nonsystematic, and dominated by random shocks rather than predictable annual cycles. This absence of seasonality has important practical implications: programme planners cannot anticipate and pre empt recurring seasonal dips, and each episode of underperformance therefore requires its own situational investigation rather than a standardized seasonal response.

5.4 Recommendations

5.4.1 Recommendations for District Health Planners

The NNAR (1, 1, 2)12 model projects a 2024 linkage to care rate averaging in the mid 80s, remaining below the UNAIDS 95 95 95 linkage benchmark. District health planners in Kampala should formally adopt the model's monthly point forecasts as performance benchmarks for 2024 quarterly reviews, triggering an immediate operational investigation whenever an observed monthly rate falls more than one standard deviation below the forecast value for that month.

Because the study found no meaningful seasonal pattern (Fs = 0.197), resource allocation and staffing plans for linkage activities should not be based on historical calendar month averages.

5.4.2 Recommendations for HIV Programme Implementers

The NNAR model's residual variance of $\sigma^2 = 87.41$ and the wide 95 percent confidence intervals confirm that a large share of monthly variation in HIV linkage to care rates cannot be explained by the series' own historical patterns. HIV programme implementers should direct attention toward the facility level and client level operational factors driving this unpredictability including inconsistent referral documentation, client mobility between facilities, insufficient follow up of HIV positive clients between testing and ART clinic attendance, and irregular data entry practices as these are likely the primary modifiable drivers of month to month volatility.

A recurrent data quality issue whereby 9.8 percent of analytic months recorded linkage rates above 100 percent due to cross month reporting lags affects the reliability of the monthly series. Programme implementers should introduce standardized same month linkage documentation protocols at all HIV testing and ART initiation points in Kampala District, aiming to ensure that at least 90 percent of HIV positive clients are recorded as linked within the same monthly reporting cycle as their diagnosis. Eliminating this source of data artefact would substantially improve the quality of future time series analyses and programme monitoring.

5.4.3 Recommendations for Policymakers and the Ministry of Health

The projected 2024 average linkage to care rate of approximately 85 to 86 percent is nearly 10 percentage points below the 95 percent target of the UNAIDS 95 95 95 framework. At the historical rate of improvement observed in the general, reaching 95 percent would require several additional years under current programme conditions.

The Ministry of Health should therefore strengthening same day linkage protocols, expanding community based ART initiation, and improving electronic tracking of clients between testing and ART clinic registration.

5.5 Limitations of the Study

The following limitations should be considered when interpreting the findings and applying the recommendations presented in this chapter.

The study uses aggregate district level monthly data, which means that facility level heterogeneity, patient level characteristics such as age, sex, distance to the nearest ART clinic, and socioeconomic status, and sub district variation in linkage performance cannot be examined.

Ten of the 102 analytic months (9.8 percent) recorded linkage rates above 100 percent due to cross month reporting lags. Although these observations were retained to preserve data integrity and to document a real systemic pattern, they introduce measurement imprecision into the monthly series and influence the estimated model parameters, contributing to the elevated residual variance ($\sigma^2 = 87.41$) and the heavy right tail of the residual distribution.

5.6 Areas for Further Research

Future research should extend this time series analysis to other districts in Uganda and to other indicators along the HIV care cascade, including ART initiation rates, retention in care, and viral suppression rates. A multi district comparison using NNAR models would establish whether the trend pattern and the absence of seasonality found in Kampala are generalizable features of Uganda's national HIV programme or specific to the urban, high service density context of the capital.

This study analysed a single aggregate district level series. Disaggregated analyses at the health sub district or facility level, using patient level or facility level monthly data where available, would reveal which facilities are driving the district average and which are consistently underperforming. Facility level NNAR models could provide the site specific, actionable intelligence that district aggregate monitoring cannot supply.

Future studies should incorporate formal interrupted time series analysis to estimate the causal impact of identifiable policy events on HIV linkage to care rates in Kampala District. Events of particular interest include the introduction of the national Test and Treat policy in 2016, the COVID 19 national lockdowns of 2020 and 2021, and the apparent moderation in the trend following the 2021 peak. Disentangling the contributions of policy change and external shocks from the underlying time series pattern would substantially deepen the explanatory power of the analysis.

The reporting lag anomaly identified in this study which caused 9.8 percent of months to record linkage rates above 100 percent warrants dedicated methodological research at the facility and patient level. Future work should develop and validate correction procedures applicable to routine DHIS2 data before time series modelling, and should quantify the size and direction of the lag at individual health facility level, providing the evidence base needed to design same month linkage documentation protocols across Uganda's HIV programme.

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