ASSESSMENT OF THE FACTORS ASSOCIATED WITH QUALITY OF ROUTINE HIV VIRAL LOAD DATA COLLECTED AT HEALTH FACILITIES IN MBEYA REGION, TANZANIA

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A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF MASTER OF ARTS IN
MONITORING AND EVALUATION
DEPARTMENT OF ECONOMICS
OF THE OPEN UNIVERSITY OF TANZANIA
2023

CERTIFICATION

The undersigned certifies that he has read and hereby recommends for acceptance by the Open University of Tanzania a dissertation titled*: **"Assessment of the factors associated with Quality of Routine HIV Viral Load Data Collected at Health Facilities in Mbeya Region"***, in partial fulfillment of the requirements for the degree of Master of Art in Monitoring and Evaluation Studies of the Open University of Tanzania.

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Dr. Harrieth Mtae

(Supervisor)

..

Date

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DECLARATION

I, **David Richard Amani**, do hereby declare that, the work presented in this dissertation is original. It has never been presented to any other University or Institution. Where other people's works have been used, references have been provided. It is in this regards that I declare this work as originally mine. It is hereby presented in partial fulfillment of the requirement for the Degree of Master of Art in Monitoring and Evaluation.

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Signature

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Date

ACKNOWLEDGEMENTS

First and foremost, praises and thanks to the God, the Almighty, for His showers of blessings throughout my research work to complete the research successfully.

I would like to express my deep and sincere gratitude to my research Supervisor Dr Harrieth Mtae for giving me the opportunity to do research and providing invaluable guidance throughout this research. Her dynamism, vision, sincerity and motivation have deeply inspired me. She has taught me the methodology to carry out the research and to present the research works as clearly as possible. It was a great privilege and honor to work and study under her guidance. I am extremely grateful for what she has offered me.

I am extremely grateful to my late Parents (Amani Mwangunule and Jacqueline Mbotta) for their love, prayers, caring and sacrifices for educating and preparing me for my future. I am very much thankful to my wife (Neema Temu) and my Sons (Jayden and Bryden) for their love, understanding, prayers and continuing support to complete this research work. Also, I express my thanks to my sisters, brother and all friends for their support and valuable prayers to complete this research successfully.

ABSTRACT

Background: Routinely collected health data are crucial for health sector planning. In developing countries, the insufficient quality of the data produced by health data systems limits their usefulness in regard to decision-making. The aim of this study was to determine level of quality of routine HIV data and associated factors in Mbeya region, Tanzania. **Methods:** This cross-sectional descriptive and analytical study included 108 health centres and their respective data clerks who were responsible for data collection in public and private health centres. The technique and tools used were an interview with a self-administered questionnaire. The dependent variables were data quality. The independent variables were socio-demographic and organizational-related factors. Bivariate logistic regression was used to identify factors associated with data completeness and timeliness. **Results**: A total of 106 data clerks with median age of 28 (IQR: 22-28) years were recruited. The level of data quality was low (44.3% for data completeness and 15.1 for data timeliness). Individual factors associated data quality were younger age (OR 1.91, 95% CI 1.66-5.45 for age 25-29 years; OR 2.39, 95% CI 1.98-5.83 for age 20-24 years) and attainment of high education level (OR 1.86, 95% CI 1.65-5.31 for diploma level; OR 1.63, 95% CI 1.51-5.21 for degree level). Organizational factors associated with data quality were access to necessary resources (OR 1.29, 95% 1.10-2.68); feedback on quality of HIV data (OR 2.14, 95% CI 1.70-6.59); Incentives (OR 1.87, 95% 1.15-4.10); monitoring quality of HIV data (OR 4.17, 95% CI 2.80-9.17); and capacity building opportunities (OR 2.39, 95% CI 1.80-7.14).

Conclusion: Data quality in terms of completeness and timeliness were very low. Individual and organizational factors should be considered when planning for interventions to improve the quality of routine HIV viral data collection.

Keywords: *HIV Viral, Load Data, Quality completeness, Timelines, Mbeya Region*

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LIST OF ABBREVIATIONS

AIDS	Acquired immune deficiency syndrome
AOR	Adjusted Odds Ratio
ART	Antiretroviral therapy
CI	Confidence Interval
DQA	Data quality assessment
HIV	Human Immunodeficiency Virus
HIS	Health Information System
HMIS	Health management information system
M&E	Monitoring and Evaluation
MoHSW	Ministry of Health and Social Welfare
NACP	National Aids Control Programs
PEPFAR	US President’s Emergency Plan for Aids Relief.
RHIS	Routine health information system
UNAIDS	United Nations Programme on HIV/AIDS
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

HIV is a significant public health challenge globally, and its impact is especially felt in sub-Saharan Africa, where most HIV-positive individuals reside (UNAIDS, 2021).). Globally, around 38.4 Million of People were living with HIV in 2021 (WHO 2021). In Tanzania, the prevalence of HIV among adults aged 15 to 49 years was estimated to be 4.7% in 2020 while Mbeya Region was the third Region with High HIV Prevalence rate in Tanzania with 9.3% in 2020 (National AIDS Control Program, 2021). Low quality of routine HIV viral load data collected at health facilities is a persistent challenge both globally and in sub-Saharan Africa (Gloyd et al., 2016; Uruena et al., 2019). Data quality issues such as missing or incomplete data, transcription errors, and inadequate monitoring and supervision systems have been reported in numerous resource-limited settings (Gloyd et al., 2016). In sub-Saharan Africa, where the burden of HIV is highest, data quality challenges remain a significant concern. Several studies conducted in sub-Sharan Africa have found that factors contributing to low data quality in the region include inadequate training of healthcare workers, poor laboratory infrastructure, limited access to viral load testing, and weak data management systems (Muthee et al., 2018; Shama et al., 2021; Siyam et al., 2021).

Access to HIV treatment is crucial for the management of the disease, and viral load monitoring is a critical component of HIV care. The World Health Organization (WHO) recommends routine viral load monitoring for people living with HIV on antiretroviral therapy (ART) to monitor treatment efficacy and to detect treatment failure early. HIV viral load testing is an essential tool for monitoring the effectiveness of antiretroviral therapy (ART) and achieving viral suppression, a crucial component of HIV treatment (WHO, 2016). Effective viral load monitoring ensures that patients receive the right treatment and care, which ultimately leads to improved health outcomes and a reduction in HIV transmission (WHO, 2017).

Mbeya is one of the regions in Tanzania with a high HIV prevalence rate, and as such, access to quality HIV viral load testing services is critical. Routine viral load testing is typically conducted at health facilities, and the data collected is used to monitor the effectiveness of ART and identify patients who require further intervention (WHO, 2016; Karami, 2019: Stephan et al., 2019). The region has several health facilities that offer HIV testing and treatment services, including viral load monitoring. Routine viral load data collected at these health facilities are essential for monitoring treatment outcomes and guiding programmatic decision-making. However, there is scarcity of evidence on the quality of the data collected at health facilities in Mbeya and other regions in Tanzania as they are often questioned, making it challenging to monitor and evaluate the effectiveness of HIV treatment and care (Leonard *et al.*, 2021).

HIV viral load testing is an essential component of HIV care and treatment. Routine viral load monitoring helps to ensure that patients are responding to treatment and allows for early detection of treatment failure, which can help to prevent disease progression and the development of drug resistance (Agnes et al., 2021). In Tanzania, HIV viral load testing is routinely conducted at health facilities, and the results are collected and reported to the national HIV program. Several barriers have been reported to prevent the effectiveness of the routine HIV data from achieving full potential in

Tanzania (Muhindo, *et al.*, 2019). Individual and organizational factors are perceived to be one of the barriers for achieving quality of electronic data collected in health systems (Alharth., 2018; Endriyas *et al*., 2019; Cheni & Roba., 2020; Sarafidis et al, 2020; Lopez et al., 2019).

High-quality data is the basis of medical research, reduces costs, and prevents medical errors, contributes to monitoring health services performance, and helps improve care quality (Mulissa et al., 2020). Assessing the quality of routine HIV viral load data collected at health facilities in Mbeya Region is, therefore, a crucial step in ensuring that patients receive optimal care and treatment. Thus, this study focuses on assessing completeness and timeliness of routine HIV viral load data collected in Mbeya health facilities and identify factors associated with data quality issues. The study identifies the gaps in the quality of the data collected and provides recommendations on how to improve data quality to ensure that the data collected is accurate and complete.

1.2 Problem Statement

Despite efforts to improve HIV treatment outcomes, there are concerns about the quality of routine HIV viral load data collected at health facilities. The accuracy of these data is crucial for monitoring treatment effectiveness and informing decisions about patient care. However, there is a lack of information on the reliability and completeness of the data, which may have implications for patient outcomes and the overall effectiveness of the HIV treatment programs (Siyam., 2021).

Therefore, there is a need to assess the quality of routine HIV viral load data collected at health facilities to identify gaps in the data collection process and recommend interventions to improve data quality. This is particularly important given the significant impact that HIV has on the health and well-being of people living with HIV, as well as the wider community. Therefore, the objective of this study is to assess the quality of routine HIV viral load data collected at health facilities in Mbeya Region, with a view to identifying areas for improvement and strengthening the quality of HIV care and treatment services in the region.

1.3 Objectives of the Study

1.3.1 Main Objective

The main objective of this study is to assess the quality of the routine HIV data collected at health facilities in Mbeya Region, Tanzania.

1.3.2 Specific Objectives

i. To identify individual factors associated with quality of the routine HIV Viral Load data collected in health facilities in Mbeya, Tanzania.
ii. To identify organizational factors associated with quality of the routine HIV Viral load data collected in health facilities in Mbeya, Tanzania.
iii. To analyze the completeness of routine HIV Viral Load data collected in health facilities in Mbeya, Tanzania.
iv. To analyze the timeliness of routine HIV Viral Load data collected in health facilities in Mbeya, Tanzania.

1.4 Research Questions

This study was guided by four main questions that were answered and these includes.

i. There is Association between the level of completeness and routine HIV Viral load data collected in health facilities in Mbeya, Tanzania.

ii. HIV routine viral load data are collected in time among health facilities in Mbeya, Tanzania.

iii. There is association between individual factors and quality of routine HIV viral load data collection in health facilities in Mbeya, Tanzania.

iv. There is association between organizational and quality of routine HIV viral load data collection in health facilities in Mbeya, Tanzania

1.5 Significance of the Study

This study is significant for several reasons. Firstly, it addresses an important issue in the management of HIV/AIDS, which is the quality of routine data collection. The study assesses the timeliness and completeness of HIV viral load data collected in health facilities in Mbeya Region, Tanzania. This is crucial for monitoring and improving the effectiveness of HIV treatment and prevention programs. Secondly, the findings of the study inform policy and practice in HIV management in Tanzania and other low- and middle-income countries. Improving the quality of routine data collection is key to achieving the United Nations' Sustainable Development Goal of ending the HIV/AIDS as a public health threat by 2030. Overall, this study contributes to the body of knowledge on HIV/AIDS management and has practical implications for improving health outcomes in resource-limited settings.

1.6 The Scope of the Study

The study focused on assessing the quality of the routine HIV Viral load data collected on health facilities by looking on level of completeness, timeliness, individual factors and organizational factors on routine HIV Viral load data in health facilities but geographically the study was carried out in Mbeya Region in which public and private health care facilities were used during the study specifically during data collection.

1.7 Limitation and Delimitation of the Study

This study was limited by a number of possible barriers including financial constraints, time limitations especially during data collection, inaccessibility of some data due to geographical location, individual characteristics as well as organizational limitations to access data for public use. These barriers were addressed through applying multiple number of the approaches to narrow the risk of data inaccessibility.

1.8 Organization of the Study

This study has been organized into three chapters in which chapter one entails to derive the background of the study including statement of the problem, objectives of the study and its significance followed by chapter two that describes theories guiding the study, literature review and the research gap. In chapter three, the research methodology lays down to approach the research problem, whereas chapter four reveals the findings of the study and discusses the findings in relation to the findings of other related studies. Chapter five concludes the study and lays down the recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

This section comprises the following key areas which includes definition of key terms, theories underpinning the study, empirical reviews, summary of literature review and research gap followed by research hypotheses and finally conceptual framework.

2.2 Definition of Key Concepts

2.2.1 Health Management Information System

Health management information system (HMIS) is a designed system that allows health data collection, storage, compilation, transmission, analysis and usage for the decision-making purpose (Rabbani, 2015). It is referring to the predominate concept of a formal and structured health information system set up to support and facilitate health management decision-making at different level of any health system (WHO, 2014). It was designed to carry both epidemiological information (health prevalence, incidence, mortality, and morbidity statistics) and administrative information (resource in put services utilization). It is comprising both Routine System and Non-Routine Systems. In Routine Health Information Systems, it involves ongoing data collection of health status, health interventions, and health resources examples; facility-based service statistics, vital events registration, community-based information systems sources. Data collected need to be processed to provide information which is crucial for decision making at all level of health service (Sanga, 2015).

2.2.2 Data Quality Assessment (DQA)

Data quality assessment is the assessment and improvement of the quality of data. It is a process involving the identification of errors, inconsistencies and other data anomalies, and conducting activities aimed at improving the quality of data and eliminating the errors identified so that the data may be useful for planning and decision making at health aspects (MoHSW, 2019).

Data Quality Assessment (DQA) is a procedure for determining whether or not a data set is suitable for its intended purpose. This assessment is an evaluation of data to determine if it is of the type, quantity, and quality needed. For the purpose of good practice in data collection, assessment is used to evaluate how effectively data are collected and if data entry complies with the minimum quality control requirements (Sanga, 2015). The purpose of data quality assessments that are performed periodically target to serve the following purposes which actually it includes purposes like verification of reported data; to provide clear indication of strengths and/or gaps in the system and to assist in planning to improve data quality; build M&E capacity to address M&E challenges found at each level of data computations (MoHSW, 2019).

Quality data are data that are reliable, accurate, precise and complete, provided in a timely manner, valid, and that maintain client confidentiality (WHO, 2017). Data quality assessment ensures that information collected and reported actually represents the program or project activities. It ensures that information is accurate and reliable, that it measures what is intended to be measured, and that it has been collected and measured in the same way (consistently) by all data collection units during all reporting periods, HSSP III (2009-2015).

2.2.3 Individual Factors

These are personal attributes that have a directly or indirectly effects on quality of routine HIV data collected at health facilities and these includes age, sex, education, experience and attitude. The data collector and users of the routine HIV data need to have confidence, motivation and competence to perform related tasks such as collection, recording, synthesizing and storing for planning and decision-making purposes. The chance of the task being performed is affected by the individual perceptions on the outcome of what is being performed and the complexity of the task being performed (Lippevel, 2019). Lack of enough knowledge on the use of data has been found to be a major drawback on the data quality and information use. Motivating health management information system’s users has remained a challenge. Despite training on data collection and data analysis, people are still having negative attitude on the data, and hence a lot needs to be done to change people’s behavior, in order to increase the performance of the routine HIV data (Sanga, 2015)

2.2.4 Organizational Factors

These are related institutional factors that influence the quality of the routine HIV data including training program, rewards/motivations, guidelines, facilities. The most important organizational factor which affects the quality of routine health data are related to structure, resource, procedure, support services and the culture which is used to develop and improve the routine health information system (RHIS) process (Lippeveld, 2000). However, there are other factors which affect the RHIS process which includes lack of funds, human resource, and management support. Having a system in place which supports data collection, analysis and transforms it to useful information will help in promoting evidence-based decision making. Thus, all components within the system are ideal in making the RHIS perform better. The effectiveness of the organizational culture is to improve RHIS performance, promoting a culture of information use, which involves the ability and control to promote values and beliefs among members of an organization by collecting, analyzing and using information to accomplish the organization’s goals and mission.

2.2.5 Data Completeness

Completeness means that an information system from which the results are derived is appropriately inclusive: it represents the complete list of records (eligible persons, facilities, units) and the fields in each record are provided appropriately (MoHSW, 2019). Data completeness was calculated by dividing the number of incomplete records by the number of records that should be reported according to each variable. Fields were considered incomplete if left blank and considered complete if there was a value reported.

2.2.6 Data Timeliness

Data are timely when they are up to date (current), and when the information is available on time. Timeliness is affected by many of factors including the rate at which the program’s information system is updated, the rate of change of actual programme activities as well as when the information is actually used or required by the users for planning purposes and decision making ((MoHSW, 2019).

2.3 Measurement and Operationalization of the Data under the Study

The data pertaining dependent variable and independent variables were measured using different approach as it has been summarized below the table as follow.

Name of the Variable	**Nature of the Data**	**Measurement of the Variable**
Dependent variables		
Data completeness	Secondary data/from health information system	Proportion of incomplete patients' information system. $Completeness = \frac{Complete\ data\ values}{All\ data\ values}$ The information includes: - Date of birth - Sex - Clinic visits - HIV diagnosis - ART regimens - Viral load tests
Data timeliness	Secondary data/from health information system	Proportion of data entered in timely manner in the patients' information system. $Timeline = \frac{Data\ \ ploaded\ on\ time}{All\ data\ values}$ The information to be checked for timelines include: - Clinic visits - HIV diagnosis - CART regimens - Viral load tests
Data quality	Secondary data/from health information system	Good quality defined as data completeness and timeliness of at least 80% of the information.
Independent variables		
Individual factors	Primary data	- Age - Sex - Education - Experience & Attitude
Organizational factors	Primary data	- Training program - Rewards/motivations - Guidelines - Resources

2.4 Theoretical Perspective

This study was guided by using one theoretical perspective known as evidence-based health information system theory.

2.4.1 Evidence Based Health Information System Theory

The study used an Evidence Based Health Information System advocated by Carbone (2008). The theory explains that there is a necessity for evidence-based information concerning the organization of day-to-day data to decide and policy formulation for any organization towards development. Carbone (2018) emphasize that there is a need to recognize the significance of having an information system that will support the implementation of new technologies in health settings hence investment on health information system cannot be underestimated. According to Evidence Based Health Information System theory data quality can be affected by different factors ranging from individual to organization

According to Carbone (2018), the notion of evidence is justified on the ground that good health care planning and decision making depends on the available health data that are being captured in a routine basis. Effectiveness of the health-related data for planning and decision making is mainly influence the level of quality of the routine health data, hence this call for evidence of the quality health data for sustainable healthcare. The theory is relevance in the sense that it provides a detailed understanding regarding quality of the health data and its applicability into healthcare planning and decision making for welfare of the people. When health data are used for different managerial purposes then there should be an evidence to prove about its usability for health sector. This theory has been objected on the ground that dimensions of assessing health data quality have not justified and this study aim to bridge this study by incorporating main dimensions of assessing the quality of routine health data measured through data completeness and data timeliness but data quality was analyzed using factors such as individual factors and organizational factors which is the focus of this study.

2.5 Empirical Reviews

2.5.1 Data Completeness

A study conducted by Abbas *et al*., (2022) about data quality and data use in primary health care in Iran whereby a cross-sectional study was conducted with participation of 348 healthcare workers in urban and rural primary health centers of the city. Data were collected by using validated self-administered questionnaire and the data into hand were analyzed using SPSS statistics software. The results from the study revealed that data quality on health care settings is defined mostly on the following dimensions which are timeliness, completeness, accuracy, security and relevance of the data. But the study also found that training healthcare workers and managers regarding health data management for decision making.

Lopez *et al*., (2019) examined the assessment of the quality of routine HIV testing data in the community setting from 2015 to 2016. The data were collected by the COBATEST Network in which content thematic data analysis were employed to establish the main determinants of data quality of routine data in the health settings. The results of the study revealed that data completeness, data transcription validity and data consistency are main variables which affects the quality of the data for planning and decision making and for this case healthcare practitioners should invest more on making sure that data are complete enough, valid and accurate before planning and making health decisions for sustainable health care services. Despite the above results there is limited information regarding the influence of individual and organizational factors towards quality of routine health data.

A study conducted by Nicol, (2017) about the assessment of the quality of routine data for the prevention of mother to child transmission of HIV in South Africa as an analytical observation using secondary data which were analyzed through STATA 13 specifically using descriptive statistics, analysis of variance as well as bland Altman analysis. The results from the study revealed that the level of completeness, data accuracy are the main key dimension under which affects the quality of the routine data but also the study recommended that other factors that may influence data accuracy includes supervision, routine health information system processes, training and relationship. This study failed to account other main dimensions that defines quality of the routine data for rational decision making in the health industry.

Shama *et al.,* (2021) assessed the quality of routine health information system data and associated factors among departments in public health facilities in Harari region Ethiopia. A cross-sectional study was conducted in all public health facilities in the Harari region of Ethiopia. The department-level data were collected from respective department heads through document reviews, interviews, and observation checklists. Descriptive statistics were used to data quality and multivariate logistic regression was run to identify factors influencing data quality. The results from the study reports that training about health management information system require heavy investment on developing skills, equipping knowledge regarding how to record, analyze and keep those data for future use specifically for planning and decision-making purposes. Also, this study revealed that the quality of the routine data is much more determined by organizational factors, technical factors and behavioral factors although operational factors also play a significant influence on quality of the routine data such as data completeness, data accuracy, timeliness as well as knowledge on health information system.

Pringle, *et al;* (2015) conducted a study that assessed the completeness and accuracy of computer medical records in four high-recording general practices, the study used secondary data set collected from documentary reviews and the results found that data in computer records were of sufficient completeness and accuracy to allow meaningful data aggregation for some diagnoses, prescriptions and referrals

2.5.2 Data Timeliness

Agnes *et al.*, (2021) carried out a study on quality of the data collection in a large HIV observational clinic database in sub-Saharan Africa. The study employed an observational HIV clinic database to answer research questions and the data collected were analyzed through content analysis and the resultant results signified that the modality of the quality of the data are mostly affected by technological as well as organizational factors such as expertise as well as equipment used to collect and store the data required. This study did not indicate other aspects through which quality of the data may be assessed such as data complete and timeliness.

Lorence, (2013) conducted a national survey of health information managers to assess among others 12 the prevalence of a standard data quality practice and the adoption of policies related to timeliness of data capture in Malawi. The study showed that, on a national level, only a slight majority of respondents indicated adoption of timeliness policies. About 61% of respondents indicated that they have policies and procedures addressing data timeliness, although persistent patterns of non-adoption were found. Timeliness of data collection should therefore be part of an overall data collection strategy that managers can employ to improve the quality of their information.

Nicol, (2017) performed a study regarding the assessment of the quality of routine data for the prevention of mother to child transmission of HIV in South Africa as an analytical observation using secondary data which were analyzed through STATA 13 specifically using descriptive statistics, analysis of variance as well as bland Altman analysis. The results from the study revealed that the level of completeness, data accuracy are the main key dimension under which affects the quality of the routine data but also the study recommended that other factors that may influence data accuracy includes supervision, routine health information system processes, training and relationship. This study failed to account other main dimensions that defines quality of the routine data for rational decision making in the health industry.

2.5.3 Individual Factors

Sanga (2015) assessed health management information system performance in health facilities in Tanzania specifically at Kyela district council. The study applied primary data set collected using four methods namely questionnaire, semi-interview, focus group discussion and documentary review. 49 sample size of the respondents were used to collect the required data for the study. The data which collected were analyzed through PRISM DEAT in which use of simple description of percentages, tables and graphs was done using excel spreadsheet. The results from the study revealed that quality of the health data is much attributed by factors including skills about health management information system, age, use of information & problem solving, the use of performance improvement tools as well as training on moral and ethical issues improves health information use for decision making. The results of the study failed to establish the key elements through which quality of routine health data may be assessed such as accuracy, timeliness, completeness and knowledge regarding health information management system.

Mboera et al., (2021) examined health data utilization and the factors influencing the performance of the health management information system at the district and primary health care facility levels in Tanzania. The study applied cross-sectional study which was carried out in 11 districts and involved 115 health care facilities in Tanzania. Data of the study were collected using an observational checklist while the data collected from the field were analyzed using thematic content analysis approach to synthesize and triangulate the responses and observations so as to capture more information required.

The results from the study revealed that inadequate analysis and poor utilization practices were common in most districts and health facilities in Tanzania. Inadequate human and financial resources, attitude, lack of experience and incentives and supervision, and lack of standard operating procedures on data management were the significant challenges affecting the health management information system performance in Tanzania. In other side, the study failed to examine the ground under which assessment of the routine health related data are based on. This study, therefore this study ought to assess the main dimensions under which quality of routine health data are based for health planning and decision making.

2.5.4 Organizational Factors

A study conducted by Gonete *et al*., (2018) in Nigeria reported that the quality of routine HIV data collected at health facilities are much more attributed by factors such as technological capabilities and other infrastructural networks that support the whole process of collection, analyzing and informing to the user for the purposes of facilitating decision making and planning into health care industry.

Rabbani, (2015) examined the main aspects which influence the accuracy of health data utilization and the factors influencing the performance of the health management information system at the district and primary health care facility levels in Nigeria. The study applied cross-sectional study which was carried out in 20 districts and involved 40 health care facilities. Data of the study were collected using an observational checklist while the data collected from the field were analyzed using thematic content analysis approach to synthesize and triangulate the responses and observations so as to capture more information required.

The results from the study revealed that inadequate analysis and poor utilization practices were common in most districts and health facilities in Nigeria. Inadequate human and financial resources, attitude, lack of experience and incentives and supervision, and lack of standard operating procedures on data management were the significant challenges affecting the health management information system performance in Nigeria. In other side, the study failed to examine the ground under which assessment of the routine health related data are based on.

Lippeveld, (2000) conducted a study regarding the effect’s organizational determinants towards the quality of the routine HIV data in Italy using secondary data collected through documentary review and other published articles and journals. The data collected were analyzed using thematic content analysis in which the results from the study reported that the quality of the routine HIV data in the region is much more determined by the factors like level of technical set up of the country, facilities and training program that an organization is undertaking for the workers but a factor motivation to the workers were reported to be statistically insignificant to influence the quality of the data. The results of this study did not indicate the sample used under the study but the using only one approach to collect data for the study might have been associated with some number of errors and invalidity of the results hence this study ought to merge this gap.

2.6 Policy Review

The National guideline for the management of HIV and AIDS emphasis on improving the quality of routine HIV data collection so that they can be used to improve treatment outcomes. It provides the guidelines for testing, linking patient to care, and monitoring the viral load to HIV patients. Its strength is that it highlights the guides for both in the facilities and the community hence can be widely applied. One weakness of this guideline is that it does not address anything on how individual and organizational factors can be used to improve the quality of routine HIV data collection to inform patient care.

2.7 **Summary of Literature Review and Research Gap**

A number of studies have been conducted to assess the dimensions under which quality of the routine data for HIV are based on. Few studies have confirmed that quality of the routine data assessed by factors such as behavioral determinants, organizational determinants and technical determinants but generally it has been reported that data completeness, timeliness, accuracy, reliability, precision, integrity as well as confidentiality are the main determinants of quality routine health data while other reports differently.

The results from the past studies show that data completeness has influence on quality of the health data (Abbas *et al*,. 2022; Amani *et al*., 2015; Karami, 2019; Nicol *et al*., 2012; Gonete *et al*., 2018; Sarafid, 2020; Anderson, 2006 & Leonard *et al*., 2021). However, other studies found that data completeness has no influence on quality of routine health data (Yates, 2020; Kumar, 2019; and Shama *et al*., 2021).

Furthermore, a study conducted by Chibolu *et al*., (2019); Singh *et al*., (2017); Biley, (2020) Mboera *et al*., (2021); Lopez *et al*., (2019) revealed that data timeliness and data accuracy have a significant positive effect on the quality of the routine data. Ayele (2020) reported that data timeliness is statistically and negatively significant effects on data quality but Muhindo *et al*., (2019) reported that data accuracy and timeliness have positive effects on routine data health while a study conducted by Agnes *et al.,* (2021) revealed that routine health data is not determined by data timeliness rather than individual and organizational determinants including technical factors. Basing on the reviewed studies, there is a doubtful, mixed up of the results and some did not include many variables which measures quality of the routine health data. More enough, most of these studies have been conducted in developed countries but few in developing countries including Tanzania. In particular, this study fills the gap through assessing the influence of individual and organizational factors specifically on quality of the routine health data.

2.8 Conceptual Framework

The dependent variable is data quality with two dimensions (completeness and timeline). According to literature, data quality can be influenced by both individual and organizational factors as indicated in Figure 2.1.

Independent Variables Dependent Variable

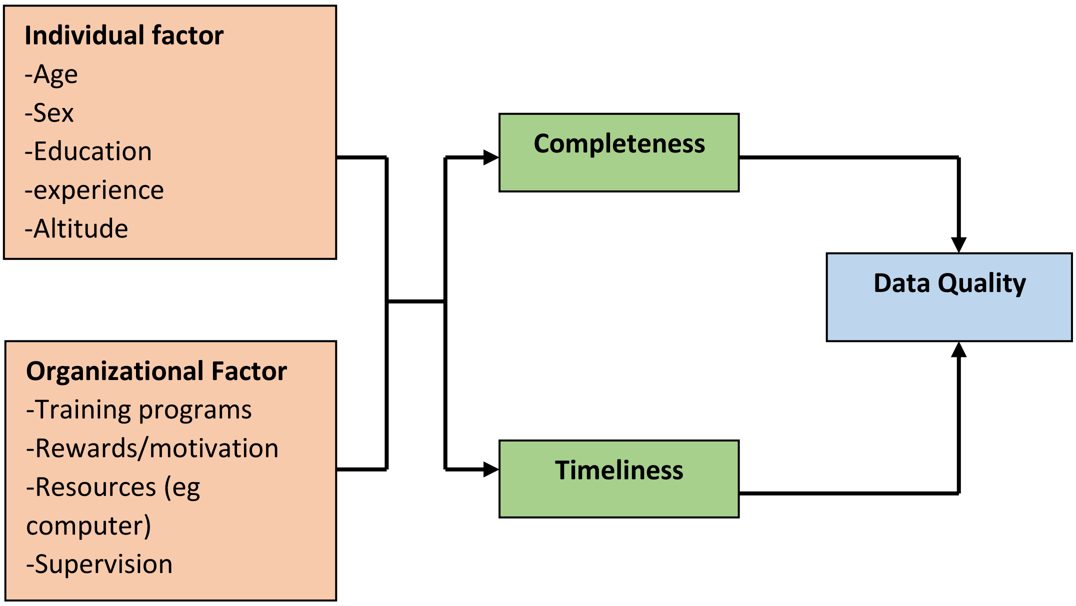

Figure 2.1: Conceptual Framework on Quality of Routine HIV Data and its Dimensions

Source: Modified Conceptual Framework Based on Sanga (2015

CHAPTER THRE

RESEARCH METHODOLOGY

3.1 Overview

After reviewing different literature in the previous chapter, this chapter addresses the key methodological issues of the study. It presents research design, study area, study population, units of analysis, variables and their measurements, sample size and sampling techniques, types and sources of data and data collection methods.

3.2 Study Design and setting

The study employed cross-sectional study design employing quantitative approach to study extent and factors associated with quality of routine data collection whereby stakeholders for HIV viral load data in the selected facilities were interviewed. A documentary review of viral load for the past six months was also be performed to determine the level of completeness and timeliness of the data.

The study was conducted in Mbeya region. Mbeya region is in the southern highland of Tanzania. Mbeya region was selected because is one of the regions in Tanzania with high prevalence of HIV with a prevalence rate of 9.3%. The region comprises a total of 150 facilities ranging from dispensary to zonal referral hospital.

Figure 3.1: A map of districts in Mbeya region (source: President's office Regional Administration and local government Mbeya Region Investment opportunities 2017)

3.3 Study Population

The study population comprised data clerks from health facilities in Mbeya region. From the health facilities, HIV-viral load data for the past six months were extracted. Data clerks (individuals assigned to perform the activity of collecting and managing data) were selected from each of the facility for the interviews.

3.4 Sample Size and sampling procedure

Sample size for this study was estimated using Kothari (2004) formula. Since the level of completeness and timelines of the data is not known in Tanzania, a proportion (p) of

50% with 95% confidence interval and margin error of 5% was used in estimating the sample size of health facilities. The formula for estimating the sample size is presented below:

$$n = \frac{\frac{z^2 p(1-p)}{e^2}}{1 + \frac{1}{N}\left(\frac{z^2 p(1-p)}{e^2} - 1\right)}$$

Whereby

Z is the z-score for 95% confidence level (z=1.96)

p measures level of data quality (assumed to be 50%=0.5)

e is the margin error (set at 5%=0.05)

N is the population size (Number of health facilities in Mbeya=150)

Applying the formula above, the estimated sample size for this study was 108 facilities.

This study utilized two stage sampling procedures. At first stage, a simple random sampling was employed to select facilities to be included for this study. At the second stage, one data clerk was selected from each of the facility included at stage 1.

3.5 Data types and data collection methods

This study used both secondary data and primary data. Secondary data comprised of routine HIV viral load data. The data on viral load that contained patients' information's and the time they were submitted from the health facilities were extracted from HJFMRI system. Secondary data provided information on the level of data completeness and timeliness. Primary data were collected on the factors associated with quality of HIV routine data collection. A questionnaire was used to collect individual factors and organizational factors that may have influence on the quality of routine data.

3.6 Data Processing and Analysis Procedure

Quantitative data was processed and analyzed using STATA version 14. Both descriptive and inferential analyses were performed. Descriptive analyses were used to summarize socio-demographic characteristics, facility information and level of data quality dimensions. A bivariate logistic regression were performed to determine individual factors as well as organizational associated with the quality of HIV routine data. A p-value less than 5% was be considered significant.

CHAPTER FOUR

RESEACH FINDINGS AND DISCUSSION

4.1 Overview

This chapter presents data analysis, presentation, and discussion. Within this chapter, a detailed analysis of findings in line with the objectives are presented.

4.2 Participants' information

A total of 106 data clerk with median age of 28 (IQR: 22-33) were recruited. Table 4.1 summarizes the information for participants and facilities. Most of the participants were male (69.8%), had diploma level of education (52.8%), and from dispensary (68.9%). Furthermore, most of the results show that most of the facilities uses both paper and electronic method of collecting data (82.1%), review and analyzed HIV viral load data on monthly basis (78.3%), use HIV viral load data regularly to inform patient care (81.1%), has access to necessary resources for ensuring data quality (85.8%), provide feedback on data quality (84.0%), and offer opportunities for capacity building (84.9%).

Table 4.1: Participants and facilities information (n=108)

Variables	n (%)
Age (years): Median (IQR)	28 (22-33)
20-24	23 (21.7)
25-29	43 (40.6)
30-35	40 (37.7)
sex	
Male	74 (69.8)
Female	32 (30.2)
Education	
Certificate	21 (19.8)
Diploma	56 (52.8)
Degree	29 (27.4)
Experience (years) on HIV data collection	
1-2	54 (50.9)
3 and above	52 (49.1)
Facility type	
Dispensary	73 (68.9)
Health centre	21 (19.8)
Hospital	12 (11.3)
Number of trainings on HIV data collection	
1	55 (51.9)
2	30 (28.3)
3 and above	21 (19.8)
Model of collecting HIV viral load data	
Paper-based	9 (8.5)
Electronic	10 (9.4)
Paper and electronic	87 (82.1)
Frequency of reviewing HIV viral load data	
Monthly	83 (78.3)
Quarterly	23 (21.7)
Use HIV viral load data to inform patient care	
Regularly	86 (81.1)
Occasionally	20 (18.9)
Has access to necessary resources	91 (85.8)
Received feedback on quality of HIV data	89 (84.0)
Ever received incentives	43 (40.6)
There is a designated team for monitoring quality of HIV data	98 (92.5)
There are capacity building opportunities	90 (84.9)

4.3 Level of routine HIV viral load data completeness

Figure 4.1 shows that the level of completeness of HIV viral load data was 44.3%. This level of data completeness is very low compared to data completeness reported in other parts of Africa such as Ethiopia (Shama et al., 2021) and Nigeria (Bhattacharya et al., 2019). The study by Shama and colleagues found out that the data content completeness was 69.6% which was still declared lower than the required 93%. The low level of data completeness indicates lack of commitment to the quality of the routinely collected data. The findings of this study are also in line with the study by Rumisha et al. (2020), who found that, despite the efforts put in strengthening health management information systems in Sub-Saharan Africa to improve data accessibility to decision-makers, the quality of data is still considerably low.

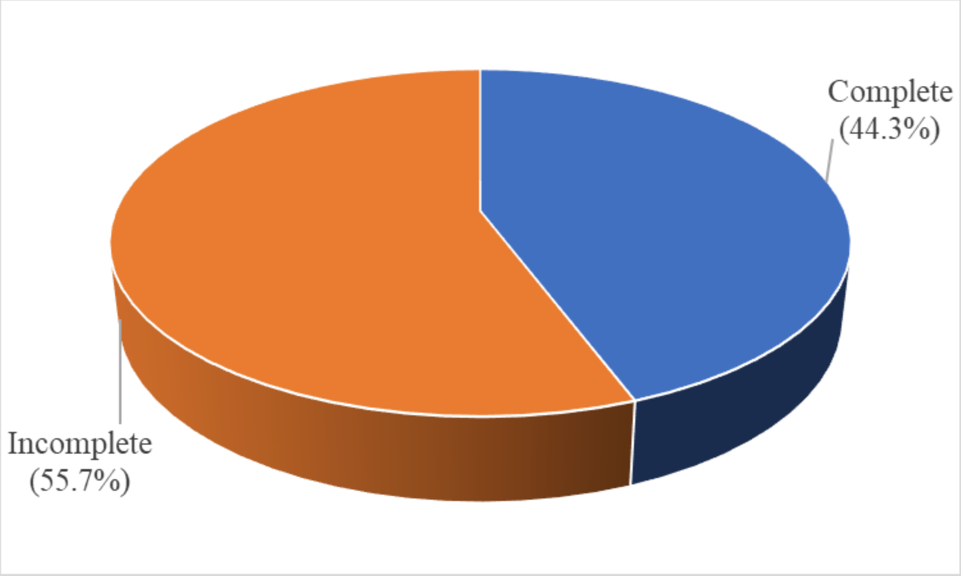

Figure 4.1: Level of HIV viral load routine data completeness

4.4 Level of HIV routine data timeliness

Results in Figure 4.2 show that data timeliness was very low (only 15.1% of the data had good timeliness). This implies that more than 80% of the routine HIV viral load data are not submitted on time, hence maybe outdated and not suitable to inform the timely patient care. This level of data timeliness was very low compared to the 93.7 percent timeliness of the data reported in Harari region of Ethiopia (Shama et al., 2021). This challenge of lack of timely and thorough data, has also been reported to affect quality of care, planning and management systems in many African countries (Ayele et al., 2021; Haftu et al., 2021), which, for the better future, needs to be addressed.

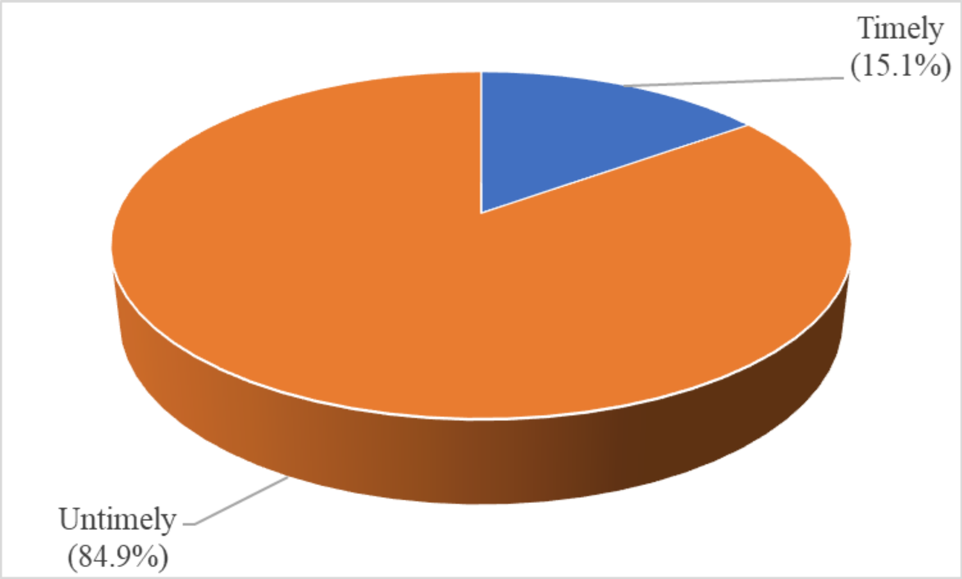

Figure 2.2: Level of HIV routine data timeliness

4.5 Individual factors associated with data quality

Table 4.2 summarizes the results of the bivariate analysis of individual factors associated with HIV routine data quality. Two individual factors (age and education) were found to have significant association with quality of routine HIV data.

Young data clerks were more likely to have good quality data compared to old data clerk (OR 1.91, 95% CI 1.66-5.45, p=0.002 for age 20-24 years; OR 2.39, 95% CI 1.98-5.83; p<0.001 for age 25-29 years when compared to those aged 40-35 years). This is because younger people might have more technological skills for crosschecking the quality of the data compared to older participants. Similar findings were reported the study by Binyam Tilahun et al (2021). This means that interventions to improve the quality of the data should be tailored by the age of data clerk.

In term of education, participants with diploma and degree level were more likely to have good quality data compared to participants with certificate level of education (OR 1.86, 95% CI 1.65-5.31, p=0.004 for diploma level; OR 1.63, 95% CI 1.51-5.21, p=0.015 for degree level). These findings are in line with those reported in a study by Solomon et al. (2021) who found that knowledge of content of Health management information system (HMIS) forms and data quality checking skill was important factors for data completeness. Similar findings were also reported by the study conducted in Western Ethiopia whereby the presences of trained staff were significantly associated to the data quality (Chekol et al., 2023; Teklegiorgis et al., 2016). The findings implies that individual education should be emphasized when it comes to improvement of data quality.

Table 4.2: Individual factors associated with HIV routine data quality (n=108)

Variables	**N**	**Good quality n (%)**	**OR (95% CI)**	**p-value**
Age (years)				
20-24	23	11 (47.8)	1.91 (1.66-5.45)	0.002*
25-29	43	23 (53.5)	2.39 (1.98-5.83)	<0.001*
30-35	40	13 (32.5)	Ref.	Ref.
Sex				
Male	74	30 (40.5)	Ref.	Ref.
Female	32	14 (43.8)	1.06 (0.72-2.83)	0.823
Education				
Certificate	21	7 (33.3)	Ref.	Ref.
Diploma	56	27 (48.2)	1.86 (1.65-5.31)	0.004*
Degree	29	13 (44.8)	1.63 (1.51-5.21)	0.015*
Experience (years) on HIV data collection				
1-2	54	25 (46.3)	Ref.	Ref.
3 and above	52	22 (42.3)	0.85 (0.39-1.83)	0.680
Number of trainings on HIV data collection				
1	55	25 (45.5)	Ref.	Ref.
2	30	12 (40.0)	0.80 (0.32-1.97)	0.628
3 and above	21	10 (47.6)	1.01 (0.40-2.99)	0.866

4.6 Organizational factors associated with HIV routine data quality

Table 4.3 presents the results for bivariate analysis for the organizational factors associated with quality of routine HIV data quality. Organizational factors associated with HIV viral load data quality were access to necessary resources, feedback on the quality of data, data quality monitoring systems, and availability if capacity building opportunities.

Facilities with access to required resources had higher odds of having good quality data compared to facilities reporting to have no access to all required resources (OR 1.29, 95% CI 1.10-2.68, P=0.045). This is not a surprising finding because it is expected that facilities that are well equipped with resources (e.g computer) are likely to produce good quality data. The findings suggest that to achieve a good quality data, investment on the required resources is invertible. Our findings are supported by Abajebel et al. (2011) and Joshua et al. (2015) who recommended that computerized HMIS data base should be used as it helps to improve data accuracy, timeliness of report and reduces the burden of data collectors.

Providing feedback on the quality of data was associated with good HIV data quality. The odds of having good quality data were twice as high for facilities that had mechanism for providing feedback on the data quality compared to facilities that did not have (OR 2.14, 95% CI 1.70-6.59, P<0.001). This implies that feedback should be integrated as part of the routine data collection. Our findings are supported by a scoping review (Lemma, et al., 2020) on improving quality and use of routine health information system data in low-and middle-income countries.

Incentives was another organizational factor associated with quality of routine HIV data. Facilities that provided incentives for data collection were nearly two times more likely to have good quality data compared to facilities that did not provide incentives (OR 1.87, 95% CI 1.15-4.10, p=0.019). This might be because different incentives could have motivated data clerk and hence increase the productivity. The findings are supported by a study by Panteloni et al. (2015) who revealed that lack of on job incentives was one among other factors that hinder timely data entry.

Systems to monitor quality of routine HIV viral load data collection was strongly associated with good quality. Facilities with systems to monitor the quality of data collection were four times more likely to have a good quality data compared to facilities that did not have (OR 4.17, 95% CI 2.80-9.17, p<0.001). This is supported by the findings from the study conducted in Gurage Zone in which the supervision was associated with the community health information system performance (Mathewos and Worku, 2015). In most cases, the quality of data improves especially when there is a routine monitoring rather than just finding faults.

Capacity building opportunities within the organization was another factor associated with data quality. Facilities that offered opportunities for capacity building were more than two times to have a good quality data compared to facilities that did not offer opportunities for capacity building (OR 2.39, 95% CI 1.80-7.14, p=0.001). The findings are in line with the findings by Abajebel et al. (2011) who found out that continuous training is important to create awareness and to have trained staff and skilled human resources that are confident and motivated for better data quality. This implies that to enhance the good quality of routine HIV data, capacity building for individuals involved should be emphasized.

Table 4.3: Organizational factors associated with HIV routine data quality

Variables	N	Good quality n (%)	OR (95% CI)	p-value
Facility type				
Dispensary	73	29 (39.7)	Ref.	Ref.
Health centre	21	11 (52.4)	1.37 (0.63-3.43)	0.124
Hospital	12	7 (58.3)	1.92 (0.71-4.34)	0.081*
Model of collecting HIV viral load data				
Paper-based	9	6 (66.7)	Ref.	Ref.
Electronic	10	5 (50.0)	0.50 (0.08-3.21)	0.465
Paper and electronic	87	36 (41.4)	0.35 (0.08-1.50)	0.159
Frequency of reviewing viral load data				
Monthly	83	37 (44.6)	Ref.	Ref.
Quarterly	23	10 (43.5)	0.96 (0.38-2.43)	0.925
Use HIV data to inform patient care				
Regularly	86	40 (46.5)	1.61 (0.59-4.44)	0.353
Occasionally	20	7 (35.0)	Ref.	Ref.
Access to necessary resources	91	40 (44.0)	1.29 (1.10-2.68)	0.045*
Feedback on quality of HIV data	89	42 (47.2)	2.14 (1.70-6.59)	<0.001*
Incentives	43	23 (53.5)	1.87 (1.15-4.10)	0.019*
Monitoring quality of HIV data	98	6 (75.0)	4.17 (2.80-9.17)	<0.001*
Capacity building opportunities	90	10 (62.5)	2.39 (1.80-7.14)	0.001*

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Overview

The challenges associated with data quality make health management information systems an ineffective tool for monitoring health data and as a source of data for planning and decision-making. Findings from this study emphasize the importance of investing in continuous data quality auditing exercises and innovating strategies that consider the underlying data management processes.

5.2 Conclusion

5.2.1 In this study we found that data completeness was sub-optimal (below 50%).

5.2.2 We found that most of the HIV viral load collected in health facilities in Mbeya are not timely. Only 15% of facilities had data that were timely.

5.2.3 Two individual factors (age and education) were associated with a quality of routine HIV viral data collection.

5.2.4 Organizational factors associated with quality of HIV data were access to necessary resources, feedback on the quality of data, data quality monitoring systems, and availability of capacity building opportunities.

5.3 Recommendations

5.3.1 The Ministry of Health in collaboration with the health facilities invest on training staff at all levels of the health system, improving quality of data-focused supportive supervision, ensuring internal data quality reviews, and encouraging data use to inform policy. This should also be accompanied by employing data clerks with proper skills as well as equipping the data clerks with required resources for quality data such as computers.

5.3.2 Systems to monitor quality of data collection should be integrated in the health facilities.

5.3.3 Capacity building, supportive supervision feedback and incentives should be given high consideration in order to improve data completeness and timeliness.

5.3.4 The guideline for ensuring data quality should be developed and should be used together with the national guideline for the management of HIV and AIDS to ensure better patient outcomes.

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APPENDICES

APPENDIX 1: QUESTIONNAIRE FOR DATA CLECKS AT HEALTH FACILITIES

My name is David Amani a student from Open University of Tanzania pursuing a Masters of Arts in Monitoring and Evaluation. I am conducting research on the quality of routine HIV data collected at health facilities in Mbeya. The findings from this study have a potential improve the quality of data and help in informing decisions in HIV programs. You have been selected as one of the participants in this study. No personal identifiers will be collected, and data will only be used for scientific purposes. Participation for this study is entirely voluntary (i.e you can decide to participate or not). If you decide to participate, the interview will take about 10-15 minutes.

Agree……………………….1 (Proceed)   Decline ……………..2 (END)

Questionnaire ID…………….

Name of facility………………

Type of facility

1. Dispensary
2. Health center
3. Hospital

Objective 3: Individual factors associated with quality of routine HIV viral load data

SECTION A: Demographics

1. Sex

1) Male
2) Female

2. What is your age (years)………………….

3 What is your highest level of education

1) Primary education
2) Secondary education
3) Certificate
4) Diploma
5) Degree
6) Postgraduate (masters etc)

4. What is your current position in the health facility?

1) Data clerk
2) IT personnel
3) Nurse
4) Medical Officer
5) Other (specify)………………………………………

SECTION B: Knowledge and Training

5 Have you received training on how to collect HIV related data?

1) Yes
2) No

6. If Yes, how many times have you received training in the last year?

1) Once
2) Twice
3) Three times
4) More than three times

7. Have you ever received training on how to analyze and interpret HIV data?

1) Yes
2) No

8. How comfortable are you with collecting HIV-related data?

1. Very comfortable
2. Somewhat comfortable
3. Neutral
4. Somewhat uncomfortable
5. Very uncomfortable

SECTION C: Attitudes and perceptions

9. How Important do you think the quality of HIV Viral load data is for the Health facility?

1) Important
2) Very Important
3) Somehow Important

4) Not Important

10. How motivated are you to collect HIV viral load data?

1) Very motivated
2) Not motivated
3) I don’t know

11. How confident are you in your ability to collect accurate and complete HIV Viral load data?

1) Confident
2) Very confident
3) Neutral
4) Somehow unconfident
5) Very un-confident

12. How comfortable are you with collecting HIV related data?

1) Very comfortable
2) Somehow comfortable
3) Neutral
4) Somehow uncomfortable
5) Very uncomfortable

SECTION D: Experience and practice

13. How many years of experience do you have in collecting HIV related data?..............

14. How is HIV Viral load data collected at your facility?

1) Paper based
2) Electronic
3) Both

15. How often is HIV Viral load data reviewed and analyzed at your facility?

1) Monthly
2) Quarterly
3) Annually
4) Rarely
5) Never

16. How often do you check for data completeness and timeliness?

1) Very often
2) Rarely
3) Never

17.How does your facility use HIV Viral load data to inform patient care?

1) Regularly
2) Occasionally
3) Rarely
4) Never

Objective 4: Organizational factors associated with quality of routine HIV viral load data

18. Do you feel you have access to necessary resources (such that equipment, supplies and support staff) to collect high quality HIV Viral load data?

1) Yes
2) No

19. Have you ever received feedback from your supervisor on the quality of HIV data that you collect?

1) Yes
2) No

20. If yes how useful was the feedback helping you to improve quality of HIV Viral load data collected?

1) Very usefully
2) Somehow useful
3) Not useful

21. Have you ever been incentivized for collecting high quality of HIV Viral load data?

1) Yes
2) No

22. If yes how did the incentives such as Bonus recognition or promotion motivate you to collect high quality HIV Viral load data?

1) It motivated me a lot
2) It somehow motivated me
3) It did not motivate me at all

23. Is there a designated team responsible for monitoring the quality of HIV Viral load data at the facility?

1) Yes

2) No

24. Does the facility have Standard Operating procedure (SOP) for managing HIV Viral load data?

1) Yes
2) No

25. Are there on going opportunities for capacity building in data management and HIV Viral load testing for Health care workers in your facility.

1) Yes
2) No

26.If yes what are the opportunities available?

1) On job training
2) Short courses
3) Refresher training

27.How do you think the quality of HIV routine data collected at your facility could be improved?

1) Improved training
2) Better access to resources
3) More feedback on data quality
4) Better incentives for high quality data collected
5) Others (Specify)

Thank you for participating in this study

APPENDIX 2: DATA QUALITY EXTRACTION TOOL

This tool was adapted from WHO and will be used to assess quality of data extracted from the system for each of the selected facility. This data will be used to measure outcome variables (data completeness and timeliness). **Objective 1** and **Objective 2** will be full addressed by information from this tool.

Part 1: Demographics

1. patient’s unique ID
2. Date of birth
3. Sex
4. Residential address
5. Contact information

Part 2: Clinical information

1. Date of HIV diagnosis
2. Current ART regimen
3. ART initiation date
4. Last viral load test date
5. HIV clinical stage
6. Presence of opportunistic infections
7. Adherence to ART
8. Date of viral load test
9. Viral load result
10. Units of measurement used
11. Laboratory performing the test

12. Test methodology

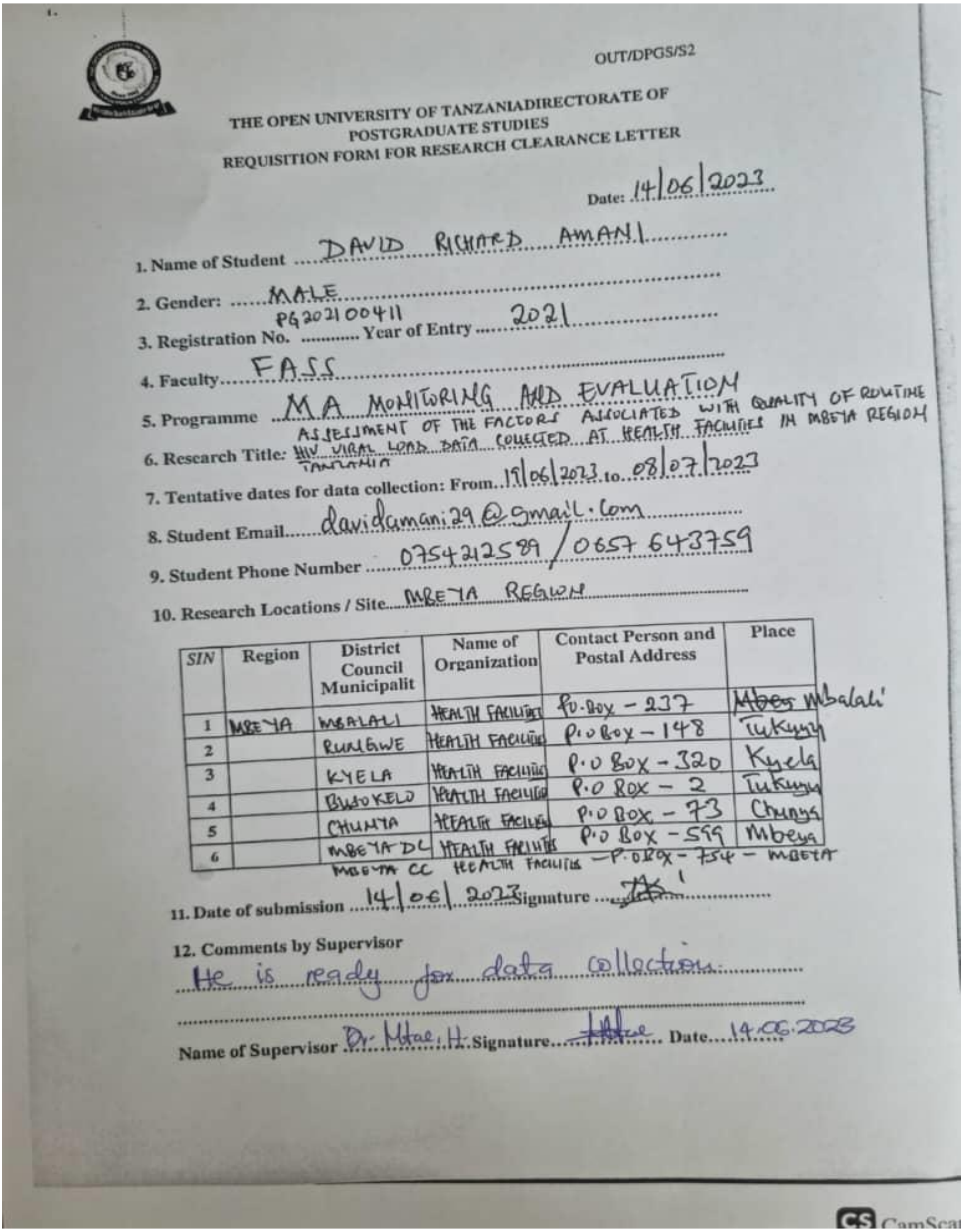
Part 3: Other

1. Date of last visit to health facility
2. Reasons for missing viral load test data (if applicable)
3. Patient’s current status (i.e still receiving ART or lost to follow-up)

Part 4: Data quality

1. Completeness of data (all fields are complete, no missing values)
2. Timeliness of data (data entered in a timely manner)

APPENDIX III: RESEARCH CLEARANCE FORM



OUT/DPGS/S2

THE OPEN UNIVERSITY OF TANZANIADIRECTORATE OF POSTGRADUATE STUDIES
REQUISITION FORM FOR RESEARCH CLEARANCE LETTER

Date: 14/06/2023

1. Name of Student DAVID RICHARD AMANI
2. Gender: MALE
3. Registration No. PG202100411 Year of Entry 2021
4. Faculty FASS
5. Programme MA MONITORING AND EVALUATION
6. Research Title: ASSESSMENT OF THE FACTORS ASSOCIATED WITH QUALITY OF ROUTINE HIV VIRAL LOAD DATA COLLECTED AT HEALTH FACILITIES IN MBEYA REGION TANZANIA
7. Tentative dates for data collection: From 19/06/2023 to 08/07/2023
8. Student Email davidamani29@gmail.com
9. Student Phone Number 0754212589 / 0657 643759
10. Research Locations / Site MBEYA REGION

SIN	Region	District Council Municipalit	Name of Organization	Contact Person and Postal Address	Place
1	MBEYA	MBALALI	HEALTH FACILITIES	P.O BOX - 237	~~Mbeya~~ Mbalali
2		RUNGWE	HEALTH FACILITIES	P.O BOX - 148	Tukuyu
3		KYELA	HEALTH FACILITIES	P.O BOX - 320	Kyela
4		BUSOKELO	HEALTH FACILITIES	P.O BOX - 2	Tukuyu
5		CHUNYA	HEALTH FACILITIES	P.O BOX - 73	Chunya
6		MBEYA DC	HEALTH FACILITIES	P.O BOX - 599	Mbeya

MBEYA CC HEALTH FACILITIES — P.O BOX - 754 - MBEYA

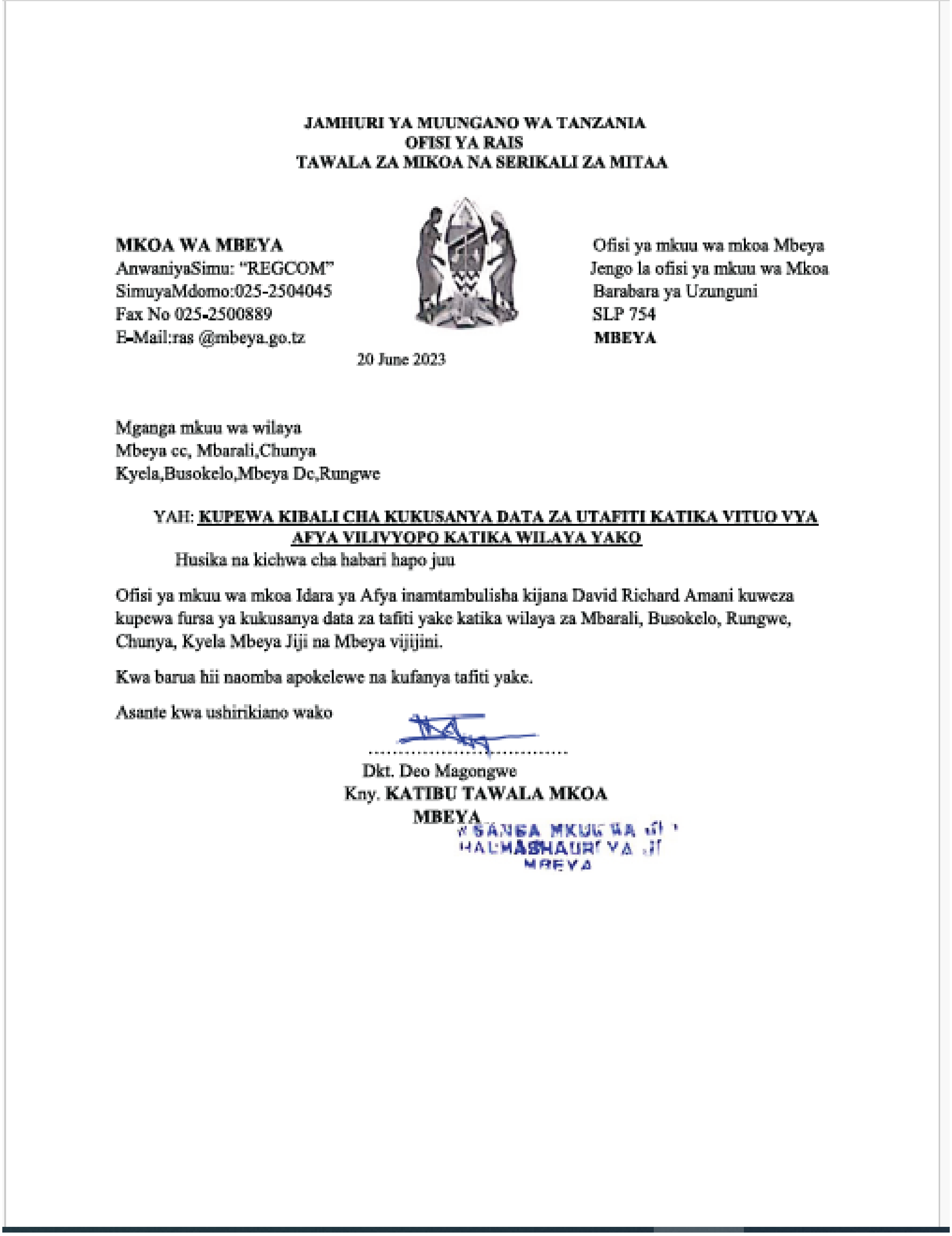
11. Date of submission 14/06/2023 Signature

12. Comments by Supervisor

He is ready for data collection.

Name of Supervisor Dr. Mtae, H. Signature Date 14.06.2023

APPENDIX IV: RESEARCH PERMIT LETTER



JAMHURI YA MUUNGANO WA TANZANIA
OFISI YA RAIS
TAWALA ZA MIKOA NA SERIKALI ZA MITAA

MKOA WA MBEYA
AnwaniyaSimu: "REGCOM"
SimuyaMdomo:025-2504045
Fax No 025-2500889
E-Mail:ras @mbeya.go.tz

Ofisi ya mkuu wa mkoa Mbeya
Jengo la ofisi ya mkuu wa Mkoa
Barabara ya Uzunguni
SLP 754
MBEYA

20 June 2023

Mganga mkuu wa wilaya
Mbeya cc, Mbarali,Chunya
Kyela,Busokelo,Mbeya Dc,Rungwe

YAH: **<u>KUPEWA KIBALI CHA KUKUSANYA DATA ZA UTAFITI KATIKA VITUO VYA AFYA VILIVYOPO KATIKA WILAYA YAKO</u>**

Husika na kichwa cha habari hapo juu

Ofisi ya mkuu wa mkoa Idara ya Afya inamtambulisha kijana David Richard Amani kuweza kupewa fursa ya kukusanya data za tafiti yake katika wilaya za Mbarali, Busokelo, Rungwe, Chunya, Kyela Mbeya Jiji na Mbeya vijijini.

Kwa barua hii naomba apokelewe na kufanya tafiti yake.

Asante kwa ushirikiano wako

....
Dkt. Deo Magongwe
Kny. **KATIBU TAWALA MKOA**
MBEYA

MGANGA MKUU WA JIJI
HALMASHAURI YA JIJI
MBEYA