INTEGRATED MACHINE LEARNING BASED QUALITY MEASUREMENT MODEL FOR MATERNAL, NEONATAL AND CHILD HEALTH SERVICES IN TANZANIA

Sarah Nyanjara

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Information Communication Science and Engineering of the Nelson Mandela African Institution of Science and Technology

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ABSTRACT

The high maternal and neonatal mortality rate has remained a challenge for most developing countries. Scholars link the high death occurrences to the poor quality of health services provided to pregnant women and children. It is further revealed that most deaths could be prevented if women and children could access high-quality maternal, neonatal and child health services. Quality measurement, a process of using data to evaluate healthcare plans and performance, is essential in improving the quality of health services and reducing mortality rates. However, most developing countries and Tanzania lack effective approaches to measure and report the quality of Maternal, Neonatal and Child Health services provided. The Lack of an effective quality measurement approach limits the quality measurement processes and may jeopardize the quality measurement results. Additionally, failure to establish the quality of health services hampers healthcare plans and governance of healthcare supplies and other resources. The available quality measurement approaches require trained data collectors, dedicated datasets and the physical presence of quality measurement personnel at each health facility; therefore, labour intensive and resource inefficient. This study proposed and developed an integrated machine learning-based quality measurement model for maternal, neonatal and child health services in Tanzania. The study employed a machine learning technique, a K-means clustering algorithm, and a dataset selected from the national health information system and data warehouse: "District Health Information System (DHIS 2)". The developed model clustered the Maternal, Neonatal and Child Health (MNCH) dataset into two groups (clusters), and cluster analysis was performed to discover the knowledge about the quality of health services in each cluster formed. The study also performed model validation to establish the usefulness of the developed integrated machine learning-based model for quality measurement in MNCH. This study brings to the body knowledge an integrated machine learning-based quality measurement model for maternal, neonatal and child health services and a list of important indicators for quality measurement, the essential inputs for an effective quality measurement process. The current quality measurement model requires only data to measure the quality of health services readily available in DHIS 2, making the quality measurement model resource-efficient and ideal for quality measurement in resource-constrained countries such as Tanzania.

DECLARATION

I, Sarah Nyanjara, do hereby declare to the Senate of the Nelson Mandela African Institution of Science and Technology that this Thesis is my original work and that it has neither been submitted nor concurrently submitted for a degree or similar award in any other institution.

24 August, 2022

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Sarah Nyanjara Date

The above declaration is confirmed by:

24 August, 2022

_______________________________ _______________________

Prof. Pirkko Nykanen Date

24 August, 2022

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Dr. Dina Machuve Date

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CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Nelson Mandela African Institution of Science and Technology a Thesis titled: "*Integrated Quality Measurement Framework for Maternal Neonatal and Child Health Services in Tanzania*", in Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Information and Communication Science and Engineering of the Nelson Mandela African Institution of Science and Technology.

24 August, 2022

Dr. Dina Machuve | Date

24 August, 2022

Prof. Pirkko Nykanen | Date

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DEDICATION

--- To my parents ---

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LIST OF ABBREVIATIONS AND SYMBOLS

AI	Artificial Intelligence
ANC	Antenatal Care
CHW	Community Health Workers
CRISP-DM	Cross Industry Process for Data Mining
DHIS	District Health Information system
DHS	Demographic and Health survey
DSR	Design Science Research
EM	Expectation Maximizing
EM	Expectation Maximizing
EmONC	Emergency Obstetrics and Newborn Care
FASQ	Facility Audit of Service Quality
FBA	Facility-Based Assessment
HFA	Facility Assessment
HFC	Health Facility Census
HINARI	Health Inter-Network Access to Research
HIV	Human Immunodeficiency Virus
ICT	Information and Communication Technology
IOM	Institute of Medicine
IPTP	Intermittent Predictive Treatment in Pregnancy
MAMA	Mobile alliance for Maternal Action
MDGs	Millennium Development Goals
ML	Machine Learning
MM	Maternal Mortality
MMR	Maternal Mortality Ratio
MNCH	Maternal, Neonatal and Child Health
MOHCDGEC	Ministry of Health, Community Development, Gender, Elderly and Children
MOHSW	Ministry of Health and Social Welfare
NGO	Non-Government Organization
NM	Neonatal Mortality
NMR	Neonatal Mortality Ratio
PCH	Population Council Health
RBF	Impact Evaluation Toolkit for Results-Based Financing in Health

RCH-co	Reproductive and Child Health Coordinator
R-HFA	Rapid Health Facility Assessment
RMNCAH	Reproductive, Maternal, Neonatal, Child and Adolescents Health
SARA	Service Availability and Readiness Assessment
SDGs	Sustainable Development Goals
SDI	Service Delivery Indicator
SMV	Support Vector Machine
SOM	Self-Organizing Map
SPA	Service Provision Assessment survey
TB	Tuberculosis
UN	United Nations
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of the Problem

Maternal Mortality (MM) and Neonatal Mortality (NM) are worldwide health challenges. However, empirical evidence reveals that the challenge is more prevalent in developing countries (Bhutta & Black, 2013; Tobergte & Curtis, 2013). All around the world, several projects and programmes have been implemented to address this challenge. Notable ones include millennium development goals (MDGs) and the current sustainable development goals (SDGs). Among other targets, MDGs emphasized improving Maternal, Neonatal, and Child Health (MNCH). In particular, MDGs intended to reduce the child mortality rate (NMR) by two-thirds (MDG 4) and maternal mortality ratio (MMR) by three-quarters (MDG 5) by 2015 (United Nations [UN], 2015). Its successor SDGs also calls for healthy lives and promoting well-being at all ages through SDGs 3 (UN, 2016). Subsequently, to improve services and mitigate the challenge, most developing countries have set MNCH care as priority agenda in the health sector (Bliss & Streifel, 2015).

Like other developing countries, Tanzania has high maternal and neonatal mortality rates and is striving to address the challenge (Bwana *et al.*, 2019). The government of Tanzania, with local and international non-governmental organizations (NGOs), development partners and other stakeholders, work tirelessly to make MNCH services available and accessible to all (Ministry of Health, Community Development, Gender, Elderly and Children [MOHCDGEC], 2016). At the national level, strategies such as a national road map strategic plan to accelerate the reduction of maternal, neonatal and child health in Tanzania (One Plan I) were implemented from 2008 to 2015. The strategy is geared toward accelerating the reduction of maternal, newborn and childhood morbidity and mortality, in line with MDGs 4 and 5 by 2015. This strategy focused on reducing maternal, neonatal and child deaths (Ministry of Health and Social Welfare [MoHSW], 2008).

The follower strategy the national roadmap strategic plan to improve reproductive, maternal, neonatal, child and adolescent health in Tanzania (One Plan II) was implemented from 2016 to 2020. Building on the progress made under one plan I, the strategy focused on guiding the implementation of reproductive, maternal, neonatal, child and adolescent health (RMNCAH) interventions in the country. The latter strategy focused on reducing maternal, neonatal, child and adolescent morbidity and mortality by offering quality services (MOHCDGEC, 2016). These strategies were followed by other projects and interventions implemented at the country level, all having the prime objective of reducing mortality rates and improving MNCH services (Moran *et al.*, 2016).

However, along with the government's and other stakeholders' efforts, maternal and neonatal mortality rates remain a health sector challenge not only to Tanzania but also to the majority of developing countries (Afnan-Holmes *et al.,* 2015; Bwana *et al.,* 2019; Pembe *et al.,* 2014; WHO *et al.,* 2015). For example in case of maternal mortality; World Health Organization (WHO) informs that "globally in 2017 approximately, 810 women died from preventable causes related to pregnancy and childbirth". The organization reported minor acceleration in reducing maternal mortality, that between 2000 and 2017, the maternal mortality ratio (number of deaths per 100 000 live births) dropped by about 38% worldwide. The WHO further notifies that 94% of all maternal deaths occur in low and lower middle-income countries and skilled care, before, during and after childbirth is said to have the potential to save the lives of women and newborns (United Nations Inter-agency Group for Child Mortality Estimation [UNIGME], 2021; World Health Organization [WHO], 2019).

In sub-Saharan Africa, statistics show that the maternal mortality rate (MMR) stands at 546 per 100 000 live births, the neonatal mortality rate stands at 28 per 1000 live births and mortality among children below five years stands at 78 per 1000 live births (Alkema *et al.,* 2016). In Tanzania mainly, the statistics show that the maternal mortality rate (MMR) stands at 556 per 100 000 live births, neonatal mortality rate stands at 25 per 1000 live births and mortality among children below five years stands at 67 per 1000 live births (Demographic and Health Survey [DHS], 2016). The high maternal and neonatal deaths in Tanzania are often linked to the poor quality of MNCH services provided to pregnant women and children (Duysburgh *et al.,* 2016). Scholars have observed that most deaths could be prevented if women and children in developing countries had access to quality MNCH care (Dalinjong *et al.*, 2018; Kinney *et al.*, 2010). Furthermore, the study by Petrucka *et al.* (2015), presented the women's voices on the poor quality of maternal care provided at health facilities in the Arusha region of Tanzania.

A situational analysis study conducted in Tanzania also revealed the poor quality of MNCH services. The analysis showed that up to two third of newborn lives could have been saved if pregnant women and newborns could have access to quality MNCH services (DHS, 2016). This alarming situation has made the Tanzanian government, NGOs and other health stakeholders focus much on MNCH care (Bliss & Streifel, 2015). Currently, in Tanzania, there are several dedicated initiatives to develop and use information and communication technology (ICT) based tools and applications to increase access and utilization of MNCH services and provide information to pregnant women and society at large for the well-being of mothers and expected newborns (Nyamawe & Seif, 2014). Examples are mobile applications that enhance nutrition information management required during prenatal and postnatal periods (Mduma & Kalegele, 2017). An interactive mobile application for Tanzania's maternal, neonatal and infant care support (Mramba & Kaijage, 2018).

Wired-mothers is a project that links pregnant women to primary health care using mobile phones in Zanzibar (Hackett *et al.,* 2018). “Health pregnancy”, “Health baby” is a text messaging service project aimed at delivering high-quality antenatal care (ANC) in Tanzania (Viljoen, 2018). Community Health Workers (CHWs) mobile application; a mobile-based tool developed by World Vision to help community health workers to provide MNCH services in Tanzania (World Vision, 2015); "Wazazi Nipendeni", a project that provides pregnancy and nursing mothers various information about pregnancy and breastfeeding (Safe Motherhood Campaign, 2015). Mobile Alliance for Maternal Action (MAMA) (Alva, 2012) and white ribbon alliance projects that campaign for safe motherhood in Tanzania (West-slevin *et al.,* 2015) are also examples of applications and projects that have been used and implemented. The projects include but are not limited to a mobile-based application like "Chipatala Cha Pa Foni", a project piloted in Balaka District in Malawi that provides MNCH care information to pregnant and nursing mothers (Rotheram-borus *et al.,* 2012; Watkins *et al.,* 2013). The "Mobile-based ultrasound" and Smartphone quantitative diagnosing solutions for anaemia detection (Crispín *et al.,* 2016; Kim *et al.*, 2018; Ross *et al.,* 2015) and websites like "Mama Ye" that provide MNCH care information (https://www.mamaye.org/countries, 2011).

Generally, significant efforts have been made to ensure coverage, access and utilization of MNCH services in countries with high maternal mortality rates and Tanzania (Nyamawe & Seif, 2014). On the contrary, recent empirical evidence is still alarming on high mortalities among women and children below five years in developing countries (Akanbi *et al.*, 2014; Akombi & Renzaho, 2019; Masaba & Mmusi-phetoe, 2020; Smith-greenaway & Trinitapoli, 2020). Several factors contribute to the poor quality of MNCH services; notable ones include; the inequalities in access to and use of MNCH services. Gaps in MNCH health services provision like birth assisted by skilled health professionals in rural and urban areas; for example, 96% of women are assisted by skilled health personnel in Kilimanjaro region, and only 45% are assisted by skilled health personnel in Simiyu region. Inadequate reproductive and maternal health care where confidentiality is not respected, and the shortage is medication supply (Lefevre *et al.*, 2018; Sageer *et al.*, 2019).

Most of the referred studies have emphasized improving the quality of MNCH services to reduce high occurrences of maternal deaths (Goyet *et al.*, 2019; Bakari, 2015; Tekelab *et al.*, 2019; WHO, 2016c). It is further observed that the quality of such services must be measured, and the results must be actionable to improve the quality of services (Kruk *et al.,* 2016b; WHO, 2018). However, most developing countries, such as Tanzania, fail to measure the quality of health services provided to pregnant women and children (Sheffel *et al.,* 2019). Most developing countries lack standards and good quality measurement approaches to measure and report the quality of MNCH services (Adirim *et al.,* 2017; Akachi & Kruk, 2017). Failure to measure and report on the MNCH quality leads to unestablished MNCH quality status, a situation that renders all efforts in quality improvement meaningless and makes it challenging to link quality improvement efforts to improved MNCH outcomes (Dettrick *et al.,* 2013). To improve MNCH quality and reduce maternal and child mortality, Tanzania and developing countries need quality measurement approaches that can effectively measure and report on MNCH quality (Kruk *et al.,* 2016b). In addressing the challenge, this study intends to develop an integrated machine learning-based model for the quality measurement of MNCH services in Tanzania.

In the current technological era, artificial intelligence (AI) technologies, especially machine learning and data mining, have increasingly been used in predicting healthcare outcomes (Wolff *et al.,* 2019). Several studies have reported using machine learning (ML) not only in predicting healthcare cost, utilization and quality (Doupe *et al.,* 2019), but also in predicting medical conditions and diseases related to maternity to avoid or mitigate the risks to both the mother and the expected newborn. Various conditions of pregnancy and childbirth such as predicting early severe maternal morbidity (Rotheram-borus *et al.,* 2012), lifetime risks of maternal death (Degninou, 2016), early hypertensive disorders during pregnancy (Poon, 2009), risk of pre-eclampsia (Neocleous, 2009) and gestational Mellitus in the first trimester of pregnancy based on biomarkers and some maternal features (Nanda *et al.,* 2011) have been predicted using machine learning. Apart from medical conditions, machine learning has also been used in different MNCH scenarios, such as analyzing the reasons behind woman's preferences for MNCH services (Jawad *et al.,* 2015). From this point of view, it is high time to deploy artificial intelligence technologies, especially machine learning, to develop an effective quality measurement approach that can measure the quality of MNCH services provided to pregnant women and children in Tanzania.

1.2 Statement of the Problem

Quality measurement is the process of using data to evaluate the performance of healthcare plans and outcomes of healthcare providers against recognized quality standards (Lazar *et al.,* 2013; Morris & Bailey, 2014). Quality measurement is essential in the process of MNCH quality improvement not only because it tells whether the services provided have high quality enough to impact the health and survival of women and children but also tells what works and what does not to improve the quality of MNCH care (Adirim *et al.,* 2017). Various tools and approaches have been developed and used for quality measurement in developing countries. Examples are Facility assessment tools such as service availability and readiness assessment (SARA) (WHO, 2014), service provision assessment (SPA) (Krüger *et al.*, 2017), service delivery indicator (SDI) (Martin & Pimhidzai, 2013) and needs assessment of emergency obstetric and newborn care have been used in assessing MNCH quality (Measure Evaluation, 2016). Also, approaches like demographic and health surveys (DHS) (Benova *et al.,* 2018; Dettrick *et al.,* 2016), quality evaluation frameworks (Bhattacharyya *et al.,* 2015; Hulton *et al.,* 2000), direct observation of clinical consultations, interview with service providers and exit interview with clients (Lefevre *et al.*, 2018) and health surveys methods (Duysburgh *et al.*, 2016; Tripathi *et al.*, 2019) to mention a few have been commonly tailored to suit various MNCH quality measurement needs.

However, the majority of the mentioned quality measurement approaches are not effective quality measurement. The approaches are manual and paper-based; hence require dedicated datasets and data collectors, the physical presence of quality measurement personnel at the health facility and physical means of quality reports dissemination to decision-making bodies. Given the financial and healthcare human resources constraints in developing countries, particularly Tanzania, the approaches impede routine MNCH quality measurement and reporting. This study aimed at automating the quality measurement process in MNCH. Specifically, the study intended to develop an integrated machine learning-based model that measures the quality of health services provided to pregnant women and children using health data collected from routine services provided at health facilities. The model is resource efficient and can work with other ICT-based systems available in the health sector.

1.3 Rationale of the Study

For the past two decades, tremendous efforts have been made to reduce mortality and morbidity among mothers and children under five years of life in developing countries (Bhutta & Black, 2013; Fotso & Tsui, 2015; Gülmezoglu *et al.*, 2016; Souza *et al.*, 2013). Despite the substantial mortality decline progress globally, the decline has been relatively low in developing countries; and Sub-Saharan Africa remains the region with the highest under-five mortality rates (WHO, 2020). It is further observed that the stillbirths decline rate in developing countries is not high enough to meet the 2030 goal of the early newborn action plan of twelve per thousand live births (12/1000) (Saleem *et al.*, 2018). Given this alarming situation, several interventions and programmes have been implemented to improve the provision and utilization of Maternal Neonatal and Child Health (MNCH) services (Austin *et al.,* 2014; Lund *et al.,* 2014). Information and Communication Technology (ICT) was one of the initiatives employed to improve the provision, utilization and access to MNCH services (Brunette *et al.*, 2011; Ismaila & Le May, 2015; Simba & Mwangu, 2004) However, along with increased utilization, access and coverage of MNCH services, maternal and neonatal mortality remain high in most developing countries (Alkema *et al.*, 2016; Fotso & Tsui, 2015; Pembe *et al.*, 2014). Several studies have linked the high mortality rates to the poor quality of MNCH services (Brenner *et al.*, 2015; Mapunda *et al.*, 2016). In this case, it is factual to conclude that increased access and utilization of MNCH services alone is insufficient to reduce maternal and neonatal deaths. The quality of provided MNCH services is paramount in reducing maternal and neonatal mortality cases (Kruk *et al.*, 2016b). Therefore, quality MNCH services should be routinely measured, and results must be actionable to enhance the impacts of MNCH services and on MNCH outcomes (Adirim *et al.*, 2017). This study envisioned automating the quality measurement process in MNCH. Specifically, the study intends to develop an integrated machine learning model for MNCH quality measurement.

Development of a machine learning-based approach is driven by; first the advances in ICT in the country, such as the use of electronic health records (EHR) and electronic medical records (EMR) like district health information system (DHIS2), which is Tanzania's national health information system and centralized database. In this system, every second, dozens of terabytes of data generated are accumulated from health facilities countrywide. The abundance of structured and unstructured data has made it possible to open new views on using available data. Second is the potential of machine learning techniques in getting meaningful insights from the abundant amount of data which helps to discover and extract hidden information.

Machine learning is part of artificial intelligence which generally refers to the ability of information technology systems to find solutions to problems by recognizing patterns in databases independently. Therefore, in machine learning, knowledge is generated based on experience. Specifically, in this study, machine learning is anticipated to enable the information technology systems to recognize patterns based on proposed and developed algorithms (learned model) and data sets extracted from DHIS2 to discover the quality of health services depicted in MNCH routine data.

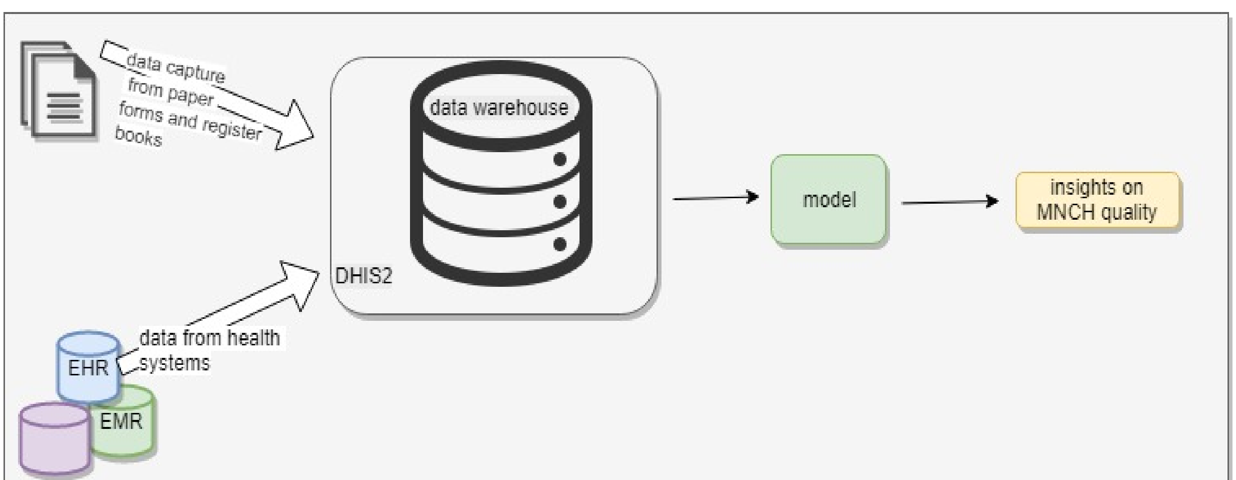

Figure 1: Block Diagram for the Proposed Quality Measurement Approach

1.4 Research Objectives

1.4.1 Main Objective

To develop an integrated machine learning-based quality measurement model for maternal, neonatal and child health services in Tanzania.

1.4.2 Specific Objectives

(i) To analyze the existing quality measurement approaches used to measure quality in MNCH care in Tanzania.

(ii) To develop an integrated quality measurement model for maternal, neonatal and child health services in Tanzania.

(iii) To validate the correctness and usefulness of the integrated quality measurement model for maternal, neonatal and child health services in MNCH quality measurement.

1.5 Research Questions

(i) What are the existing approaches used to measure the quality of Maternal, Neonatal and Child Health quality?

(ii) How best can a machine learning-based model for quality measurement in maternal, neonatal and child health services be developed?

(iii) What value is added by the developed machine learning-based model for maternal, neonatal and child health services quality measurement?

1.6 Significance of the Study

To improve MNCH quality and reduce maternal and child mortality, Tanzania and other developing countries need a quality measurement approach that can effectively measure and report on MNCH quality. Therefore, this study was worth doing because the proposed machine learning approach effectively measures and reports the quality of MNCH services. Unlike traditional quality measurement approaches, the developed quality measurement model is: (a) less prone to human errors and therefore provides more valid and reliable results, (b) resource efficient; That the developed approach uses only maternal and child health data from routine health services provision which are readily available in DHIS 2, and (c) requires fewer experts to accomplish quality measurement process, and (d) a learned quality measurement model has the potential to enhance and speed-up quality measurement process thus overcoming the costly, laborious and time-consuming task of quality measurement by traditional quality measurement approaches (v) provides safe and secure services and supports the digitization of the society.

The convince, effectiveness, and lower cost of the developed model in quality measurement Tanzania will afford routinely quality measurement and reporting, eventually will establish MNCH quality status in the country and help the ministry and other MNCH stakeholders to align new strategic plans, interventions properly, and resource allocation geared to improve MNCH services. Additionally, routinely reporting on the MNCH quality status will help determine whether the government and other stakeholders' efforts to improve quality MNCH care in Tanzania positively impact the anticipated outcomes. Also, it broadens understanding of services and interventions that significantly reduce maternal and neonatal mortality ratio, hence the proper direction of resources and efforts towards these services and interventions.

1.7 Delineation of the Study

This study proposed and developed an integrated machine learning-based quality measurement model for maternal, neonatal and child health services in Tanzania. The study employed a machine learning technique, a K-means clustering algorithm, and a dataset selected from the national health information system and data warehouse: “District Health Information System (DHIS 2)”. The developed model clustered the Maternal, Neonatal and Child Health (MNCH) dataset into two groups (clusters), and cluster analysis was performed to discover the knowledge about the quality of health services in each cluster formed. The study also performed model validation to establish the usefulness of the developed integrated machine learning-based model for quality measurement in MNCH.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

Various approaches have been developed and used to assess the quality of health services and interventions provided to pregnant women and children. Current efforts in developing and using quality measurement approaches, especially in countries with high maternal and neonatal mortality, are promising. This study proposed and developed a machine learning-based model for quality measurement in MNCH. Before development, the literature was reviewed to determine existing quality measurement approaches used for quality measurement in developing countries and Tanzania in particular. The effectiveness of existing approaches in MNCH quality measurement was analyzed to identify the gaps. Moreover, the study explored the potential of using machine learning techniques to measure health service quality. In this section, the literature review findings are summarized and presented.

2.2 Quality of Maternal, Neonatal and Child Health

There is no one universally accepted quality definition in healthcare. Scholars and organizations working in healthcare have defined it in different perceptions. Godlee (2009) defined *quality* in healthcare as "Clinically effective, safe and a good experience for the patients". Institute of Medicine defined it as "The degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge". Institute of medicine further added that quality healthcare must meet the standards of care that are; safe, effective, patient-centered, timely, efficient and equitable (Institute of Medicine [IOM], 2001).

The WHO defined quality in healthcare as the extent to which health care services provided to individuals and patient populations improve desired health outcomes (WHO, 2016c). Specifically to MNCH care, Hulton *et al.* (2000) defined *quality healthcare* as the degree to which maternal health services for individuals and populations increase the likelihood of timely and appropriate treatment to achieve desired outcomes that are both consistent with current professional knowledge and uphold basic reproductive rights. In this study, the definition by Hulton *et al.* (2000) was adopted to refer to the quality of MNCH care. The definition was adopted because it defines healthcare quality specifically to maternal, neonatal and child health.

2.3 Quality Measurement in Maternal, Neonatal and Child Health

Sustainable Development Goals (SDGs) call for a global commitment to ensuring healthy lives and promoting well-being for all ages (UN, 2016). Therefore, all the people and communities worldwide should have access to high-quality health services. As the concern for quality health care increases, the need for quality measurement also increases (Kruk *et al.*, 2018). In healthcare, *quality measurement* is defined as using data to evaluate the performance of healthcare plans and healthcare providers against recognized quality standards (Lazar *et al.*, 2013; Morris & Bailey, 2014). In Maternal, Neonatal and Child Health (MNCH) care, quality measurement is essential if the health outcomes for pregnant women and children continue improving (Akachi & Kruk, 2017; Kruk *et al.*, 2016a). Quality measurement provides insights on whether the services provided are of high quality enough to make a difference in the health and survival of pregnant women and children and also information on what works and what does not to improve MNCH care. In this view, therefore, literature was reviewed to identify quality measurement approaches currently used for MNCH quality measurement in developing countries, including Tanzania, and to analyze the effectiveness of available quality measurement approaches in measuring the quality of maternal and child health services in Tanzania.

2.4 Data Sources and Search Strategy

A comprehensive literature search was conducted from Pub Med, HINARI, ARDI and Google Scholar electronic databases. Also, a search from organizations' websites, including: World Health Organization (WHO), USAID's MEASURE Evaluation Project, and Engender health and Family Planning 2020 (FP, 2020) was conducted. The search for relevant articles was done using a "*Boolean search strategy*" with a combination of four different key terms: (a) "Quality assessment tool AND maternal health OR Neonatal health OR Child health", (b) "Quality assessment method AND maternal health OR Neonatal health OR Child health", (c) "Quality measurement AND maternal health OR Neonatal health OR Child health" and (d) "Quality evaluation AND Maternal health OR Neonatal health OR Child health". The search keywords were used for all the consulted databases.

2.4.1 Exclusion and Inclusion Criteria

To be included in a review, an article had to meet the following inclusion criteria: (a) A scholarly or a peer-reviewed article, and (b) Has an abstract or full text online, a journal article and a conference proceeding, a government document, a dissertation or a thesis. Articles written in other languages apart from English and do not have English translation, the articles that did not focus on quality assessment and those that do not describe or develop an approach that measures quality in MNCH were excluded.

2.4.2 Article Search Results

The Prisma method was employed in article screening. Three hundred and twenty-four (324) articles found from the databases were involved in the screening. Thirty-two (32) articles met inclusion criteria and were included in the review. The article selection process using the Prisma method is articulated in Fig. 2.

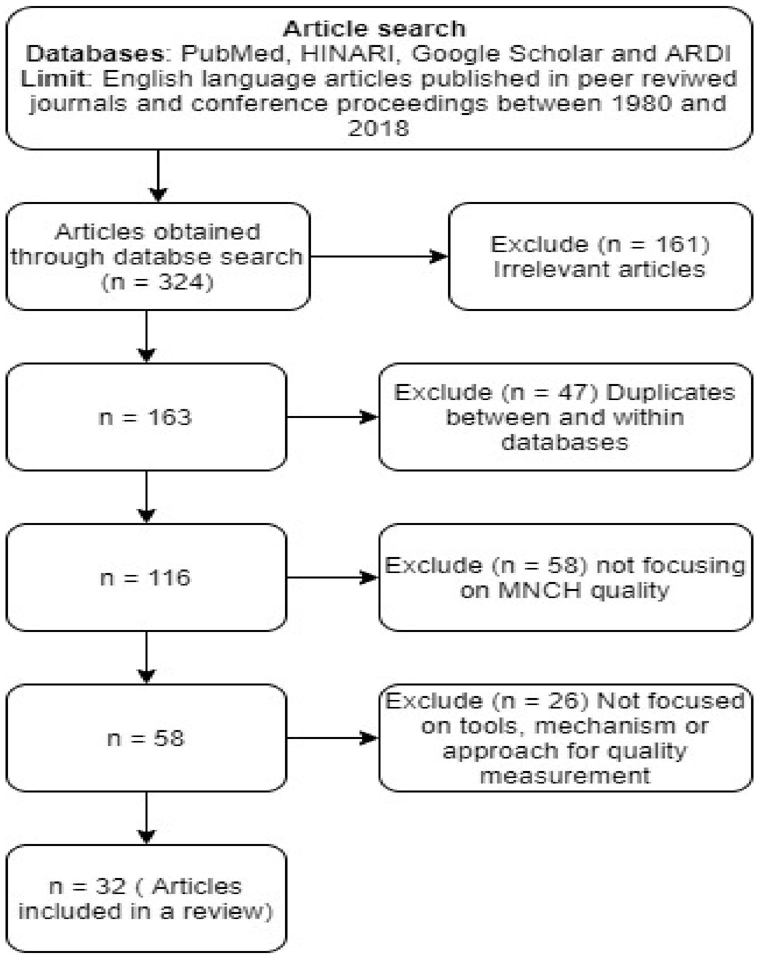

Figure 2: Article Selection Flow Chart

2.5 Approaches for Maternal, Neonatal and Child Health Quality Measurement in Tanzania

Several approaches have been developed and used to measure the quality of MNCH were identified. The review mainly focused on approaches used to measure the quality of MNCH care in developing countries, particularly in Tanzania. For better understanding, the quality measurement approaches were categorized into three groups: Tailored quality measurement approaches (Table 1), facility-based quality measurement tools and methods (Table 2) and ICT-based quality measurement approaches.

2.5.1 Facility-Based Quality Measurement Tools

This category (Table 2) includes quality measurement tools and methods used for quality measurement at the health facility level. The tools and methods in this category measure the quality of health services by assessing the ability of health facilities to provide quality health services. Therefore, to accomplish the intended goal, the tools seek information and answer the questions on the primary health facility infrastructure, capacity to provide services, medical supplies and quantities of services provided at a health facility.

2.5.2 Tailored Quality Measurement Approaches

This category (Table 1) comprises all the quality measurement approaches tailored to suit various quality measurement needs at the facility and national levels. The study found the existence of tailored quality measurement approaches developed upon special quality measurement needs from international organizations and national initiatives geared to establish and improve MNCH quality. Some approaches were developed by various projects and programmes to improve MNCH services, others were developed as research deliverables or results of the studies conducted by various scholars in the MNCH domain.

2.5.3 Information and Communication Technology-Based Quality Measurement Approaches

Although it was the desired intention of this study to find ICT-based quality measurement approaches for MNCH, among the reviewed, none of the approaches was ICT-based. However, similar to the proposed quality measurement approach, the study found a few approaches that use machine learning techniques to assess the quality of health services and healthcare content on web pages and medical blogs.

Table 1: Summary of Tailored Quality Measurement Approaches

Study(s)	Objectives	Methodology/Tool used	Data Source	Major Focus	Indicator Type
Kruk *et al.* (2016b)	Measuring the quality of basic maternal care functions in delivery facilities	Service Provision Assessments (SPA) by the Demographic and Health Survey (DHS) Programme	Demographic health survey	Maternal and neonatal	Structure and Process
Dettrick *et al.* (2016)	Creating a single "Quality Index" (QI) representing quality of maternal and neo- natal health care based on data collected. as part of the Demographic and Health Survey (DHS) program	Demographic health survey (DHS)	Demographic health survey	maternal and neonatal	Structure and Process
Canavan *et al.* (2017)	Development and testing a method of measuring the quality of maternal and neonatal care that could be embedded in a larger national performance management initiative	Direct observations and medical record reviews to score quality in nine domains of intrapartum care	Medical records review and direct observation	Maternal and neonatal	Process
Nesbitt *et al.* (2013)	Evaluating the quality of routine and emergency intrapartum and postnatal care using a health facility assessment, and estimating "effective coverage" of skilled attendance in Brong Ahafo, Ghana	Assessing the performance of key signal functions and the availability of relevant drugs, equipment and trained health professionals	Facility data	Maternal and Neonatal	Process and Structure
Pazandeh *et al.* (2015)	Investigation of the provision of care during labour and childbirth in comparison with national guidelines in four public hospitals in Tehran.	descriptive evaluation study and investigated the provision of care during labour and childbirth using current evidence-based practice as the indicator of quality	Observation and interview	Maternal	Process
Chawla and Darlow (2018)	Development of Quality Measures in Perinatal Care	Direct observation, existing records, and interview of the involved stakeholders	Direct observation, medical record review and interview	Neonatal	Process

Study(s)	Objectives	Methodology/Tool used	Data Source	Major Focus	Indicator Type
Tripathi *et al.* (2019)	Development and validation of an index to measure the quality of facility-based labour and delivery care processes in Sub-Saharan Africa	A comprehensive delivery observation checklist used in quality surveys in sub-Saharan African countries	Direct observation	Maternal and Neonatal	Process
Guzha *et al.* (2018)	Assessment of quality of obstetric care in Zimbabwe	hospital discharge data review	Medical record review	Maternal and Perinatal	Process and Outcome

Table 2: Summary of Facility-Based Quality Measurement Approaches

Tool	Data Source	Major Focus	Indicator Type
Service Provision Assessment (SPA) survey	Questioner, observation, exit interview and provider interviews	Quality of Maternal, neonatal and child health	Structure
Service Availability and Readiness Assessment (SARA)	Uses rapid data collection and analysis	Maternal, neonatal, Family planning, HIV, TB, Malaria and Child Health	Process
Needs assessment of Emergency Obstetrics and Newborn care	Health facility data	equip health facilities with the capacity to provide evidence-based, cost-effective interventions to attend to the leading causes of maternal and newborn mortality	Structure and Process
Service Delivery Indicator (SDI)	Nationally representative health data	performance and quality of service delivery in primary schools and at frontline health facilities	Structure, Process and Outcome
Impact Evaluation toolkit for results-based financing in health (RBF)	Survey and direct observation	design and implement impact evaluations, with a focus on Results-Based Financing in maternal and child health programs	Maternal and Child Health
Facility-Based Assessment (FBA)	Observation of provider performance, exit interviews with child caretakers, provider interviews, record review, and an inventory of essential equipment and supplies.	The FBA evaluates the extent to which children are appropriately diagnosed and treated at health facilities.	Structure and Process
Health Facility Census (HFC)	Facility health data	This tool assesses the physical assets in the health sector with primary design for policy, planning and management of the health system	Structure
Population Council Health Facility Assessment (HFA)	Facility health data	The Population Council HFA allows reproductive health programme managers to benchmark the performance of health facilities. The tool is primarily designed for planning purposes, especially for strategic health planning,	Structure and Process

Tool	Data Source	Major Focus	Indicator Type
		monitoring, and evaluation, although it may also be used while piloting service quality improvements	
Facility Audit of Service Quality (FASQ)	Facility health data	Assesses facility infrastructure, equipment and the quality of care provided.	Structure
Rapid Health Facility Assessment (R-HFA)	Rapid Health Facility Assessment (R-HFA) Facility health data	The R-HFA measures a small set of indicators for maternal, newborn and child health services in primary care to identify bottlenecks in service delivery.	Structure and Process

2.5.4 Analysis on the Effectiveness of Existing Quality Measurement Approaches

Apart from the identifying quality measurement approaches currently in use, the review intended to determine the effectiveness of the approaches in measuring the quality of MNCH services. The analysis was done using the following criteria: (a) Sources of data and data collection techniques for quality measurement, (b) Indicators for quality measurement and (c) Expertise and quality measurement frequency. The selection of the mentioned criteria was based on the requirements for quality measurement. A set of data is needed to measure quality because the quality measurement is the process of using data to evaluate the performance of healthcare plans and health care providers against recognized quality standards. Healthcare plans and performance evaluations must be accomplished in a particular fashion, and by an expert in given time.

2.5.5 Data Sources and Data Collection Mechanisms

Availability of quality data is the number one requirement for the quality measurement process. Each quality measurement approach requires a reliable source of quality data. The summary of quality measurement approaches shows that both facility-based quality measurement approaches rely on demographic and health surveys (DHS), direct observation, patient and health workers interviews, health facility data, exit interviews, surveys, hospital discharge records and medical records review as primary sources of data. Consequently, the major data collection tools are interview guides, observation checklists and questionnaires. However, the use of mentioned data sources and data collection techniques is associated with some challenges that, in one way or the other, contribute to the ineffectiveness of the approaches in MNCH quality measurement.

For example, the use of demographic and health surveys and other surveys data for quality measurement (Dettrick *et al.*, 2016; Hanson *et al.*, 2014; Kruk *et al.*, 2016b; WHO, 2008), is subjected to sampling bias if the population sampled is not representative of the population as a whole and response bias if the population is not represented in the responses. Nevertheless, surveys are usually done in five to ten years to allow comparability. For this reason, the approaches that use survey data must follow the time interval of five to ten years to measure the quality of health services provided to pregnant women and children.

Similarly, poor survey administration procedures may lead to poor quality data that may jeopardize quality measurement results. Additionally, data from direct observation (observation of providers' performance) is used for quality measurement (Canavan *et al.*, 2017; Chawla & Darlow, 2018; Pazandeh *et al.*, 2015; Sprockett, 2017; Tripathi *et al.*, 2019). The ability to identify whether the poor quality of health services originates from the process which was poorly implemented or from the lack of required inputs, make data from direct observation highly preferred for quality measurement (Catchpole *et al.*, 2019). However, direct observation is said to be susceptible due to observer bias, and the act of observation is also suspected to affect the performance of the process being observed (Gardner, 2014). On the other hand, the method requires an expert who will make the observations. The need for expert or trained personnel to accomplish quality measurement process add extra human resource requirements.

2.5.6 Indicators for Quality Measurement

Generally, indicators for quality measurement vary according to the nature and purpose of the quality measurement approach. Facility-based quality measurement approaches measure the quality of health services by assessing the ability of health skills to provide quality health services. Therefore, to accomplish quality measurement, the collected data are analyzed to seek information and answer the questions on the primary health facility infrastructure, medical supplies, capacity to provide services and quantities of services provided at a health facility concerning stated standards which depict the provision of quality health services. Facility-based quality measurement approaches, therefore, follow the Donabedian model for quality evaluation. Donabedian model measures the quality based on the health components' structure, process and outcome.

However, measuring the quality of health services using the structure, process or outcome indicators alone or a combination of either structure and process or process and outcome or outcome and structure may not capture some of the data needed in quality measurement. It has been observed that good input, such as a well-structured health facility with enough medical suppliers, does not automatically result in good health outcomes. Therefore, measuring the quality of health services by looking at basic health facility infrastructure, capacity to provide services and quantities of services provided at health facility alone may not provide the actual quality measurement results (Nsona *et al.,* 2016).

Similarly, measuring the quality of health services by relying on healthcare processes alone is challenged by the poor health-seeking behavior among women in developing countries. Recent evidence has shown that maternal and neonatal mortality rates are higher in health facilities because women tend to seek health care very late and not due to poor health processes at the health facilities (Kassim & Katunzi-Mollel, 2017; Qureshi *et al.,* 2016; Tull, 2020; White *et al.,* 2006). While measures based on the health outcome seem to be the gold standard in measuring quality, some scholars claim that an outcome is a result of many factors which may be beyond the provider's control. A high percentage of maternal or child mortality may be contributed by several factors which are not directly associated with healthcare structure or processes (Gebretsadik & Gabreyohannes, 2016; Sageer *et al.*, 2019).

2.5.7 Expertise and Quality Measurement Frequency

The majority of existing quality measurement approaches do not indicate expertise requirements and quality measurement frequency. However, a quality assessment approach that indicates a finite set of procedures for quality measurement requires a team of personnel to accomplish the quality assessment process. The team should include data collectors, data collectors' trainers, data analysts and other experts. Thus, the whole process needs adequate financial and human resources. In Tanzania and other developing countries, doctors and researchers in healthcare are customarily employed to measure the quality of health services. Because the whole task force comes from the healthcare sector, this is a major challenge for developing countries. Allocating the budget for quality assessment and reserving health staff to accomplish assessment is problematic due to the budgetary constraints and shortage of human resources in healthcare; this limits the quality assessment and quality assessment frequency.

2.6 Potentials of Machine Learning in Healthcare Quality Measurement

Artificial intelligence (AI) technologies, especially machine learning and data mining, are increasingly used in predicting healthcare outcomes (Sageer *et al.*, 2019; Wolff *et al.*, 2019). Several studies have reported using machine learning (ML) to predict healthcare costs, utilization of resources and quality of services (Doupe *et al.*, 2019). The ability of ML to provide insight from both structured and unstructured data makes it applicable for quality assessment in healthcare (Jiang *et al.*, 2017). Machine learning algorithms have been used, e.g. to assess the quality of healthcare services, information, and treatment provided online via the web pages and blogs (Sondhi *et al.*, 2012).

A study done by Aphinyanaphongs and Aliferis (2007) used a support vector machine (SMV) algorithm to develop a model that was used to filter and identify the web pages that do not contain quality cancer treatment information. Specifically, the model performed text categorization to identify unproven cancer treatments on the web pages. The developed model can identify web pages that make unproven cancer treatment in a fully automatic manner and substantially better than the previous web-based tools and state-of-the-art search engine technologies. The study by Sondhi *et al.* (2012) developed a supervised learning approach using the Support Vector Machine (SVMLight) toolkit. The approach was designed to predict the reliability of medical web pages automatically. The algorithm successfully classified medical webpages as being reliable or not, based on the information web page contents and features contained with the accuracy of 80%.

Further advancements in the development and use of machine learning models for quality measurement are the following: Al-Jefri *et al.* (2017) automatically measured the quality of online health information on the webpages based on their contents by applying natural language processing (NLP) and machine learning (ML) techniques. Recently, Afsana *et al.* (2019) achieved an accuracy of 84 to 90% with a data mining approach developed to automatically assess the quality of online healthcare articles based on the predefined quality criteria. Also, a machine learning model was developed using observational data to assess the quality of glycemic control care provided to patients with type II diabetes using the DIABETIMSS program (You *et al.*, 2019).

2.7 Review Summary and Research Gap Identification

The main objective of this study was to develop a model for quality measurement in MNCH services. Before developing the intended quality measurement approach, a review of existing quality measurement approaches was done with the prime objective of identifying quality measurement approaches currently available for quality measurement in MNCH. Also, the aim was to analyze the effectiveness of existing approaches in MNCH quality measurement. Thirty-two studies met the review inclusion criteria. Among these 32 articles reviewed, this study found 18 approaches for quality measurement. Eight were tailored quality measurement approaches, and 10 were facility-based quality measurement approaches used for quality measurement in developing countries and Tanzania.

Based on chosen criteria, the analysis of the effectiveness of quality measurement approaches in MNCH quality measurement was done. The review results indicate that; data sources and data collection mechanisms, indicators for quality measurement and expertise and quality measurement frequency are significant aspects that affect the effectiveness of existing approaches in quality measurement. Additionally, the review found that manual and paper-based operational modes made existing quality measurement approaches labour intensive and resource inefficient. Nevertheless, the review found that none of the found approaches is considered standard for MNCH quality measurement in Tanzania.

Given the importance of quality assessment in improving the quality of MNCH services and reducing maternal and neonatal deaths, this gap is critical. A standard quality assessment approach is a prerequisite for MNCH quality improvement. This study proposes a machine learning-based approach for quality assessment in MNCH. The proposed approach is considered adequate as it will overcome the challenges of the existing quality measurement approaches. A proposed machine learning-based quality measurement approach is thought to introduce a paradigm shift in quality measurement by streamlining, optimizing and automating the quality measurement processes. Deploying the proposed quality measurement approach will result in operational efficiency that can reduce cost and improve quality measurement processes; hence routine MNCH quality measurement and reporting.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Overview

This Chapter elaborates on the materials and methods used to accomplish quality measurement model development. Design science research (DSR) methodology was the general method deployed to undertake the study. Additionally, the study employed a cross-industry process for data mining (CRISP-DM) model to accomplish the third objective, which comprised model development. This Chapter, therefore, is divided into sections and subsections to adhere to the mentioned research methodologies.

3.2 Design Science Research Methodology

The six phases of design science research (DSR) methodology (Fig. 3) for information systems developed by Peffers (2007) as described in Fig. 4, was adapted to carry out the study. The design science research (DSR) methodology incorporates the principles, practices and procedures required to conduct research in engineering and computer science disciplines. The methodology is suitable for this study because it mainly focuses on the development and performance of the new technology product to improve the functional performance of the product (Vaishnavi & Kuechler, 2005).

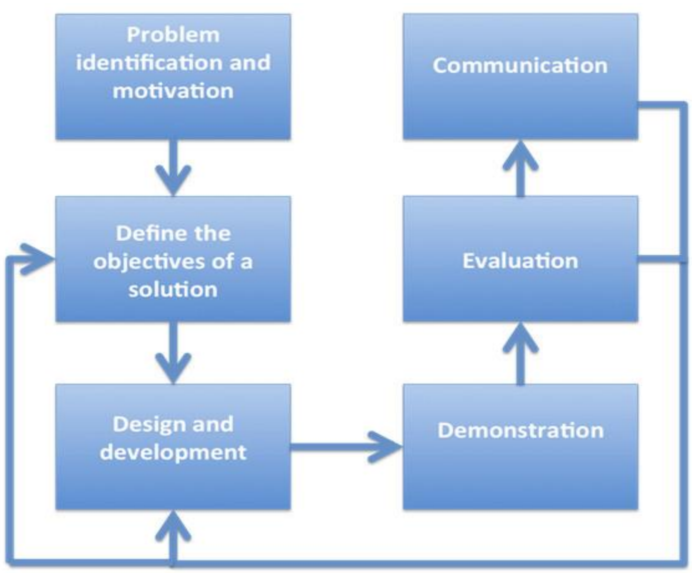

Figure 3: Design Science Research Methodology (Peffers, 2007)

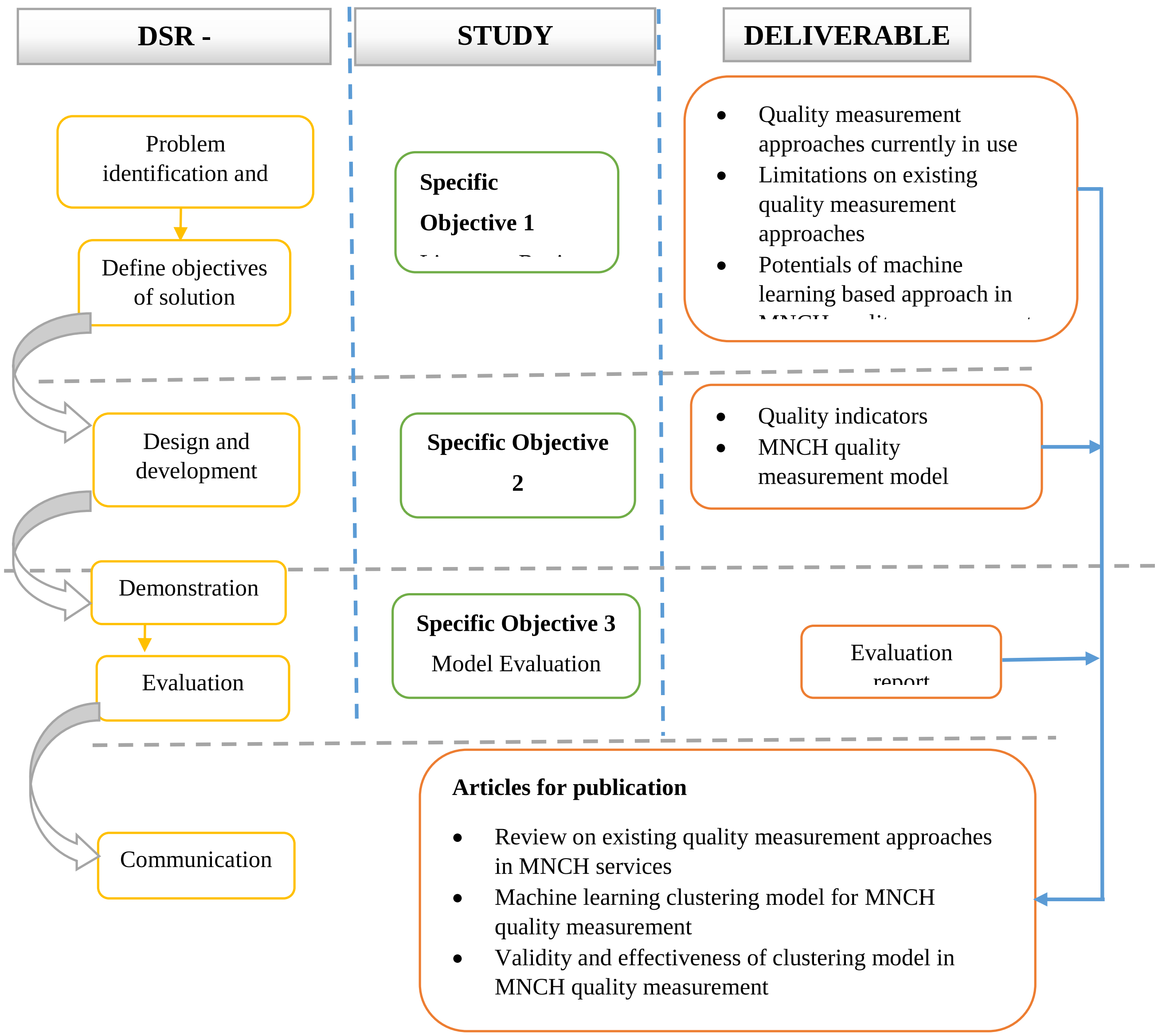

Figure 4: Mapping Design Science Research (DSR) Methodology to the Study Objectives and Deliverables

3.2.1 Phase I: Problem Identification and Motivation

The problem identification and motivation phase seek to define the specific research problem and justify the solution's value. This phase was accomplished in the first and second chapters of this study. In these Chapters, the literature on MNCH quality was reviewed, and the lack of adequate quality measurement approaches for quality measurement in MNCH was identified as a significant challenge that impedes MNCH quality improvement and reduction of maternal and child mortality in Tanzania. The quality measurement approaches in place were found to be limited by resources in healthcare as most approaches require extra financial and human resources to accomplish quality measurement. The manual and paper-based operations also made the approaches time-consuming and effort intensive. A machine learning model was proposed to address the challenges for automated and effective quality measurement in MNCH.

3.2.2 Phase II: Objective of a Solution

To address the notable limitations observed in quality assessment approaches currently in use, this study proposed and developed a machine learning-based model for effective quality measurement in MNCH. Therefore, the study developed a clustering model using the K-means algorithm that will use maternal, neonatal and child health data from routine health services in Tanzania. The model identifies the patterns (cluster) from the dataset, then clusters data points into respective clusters and then evaluates the clusters to discover the knowledge about the quality of health services portrayed in each cluster. Figure 5 illustrates the general objective of a solution.

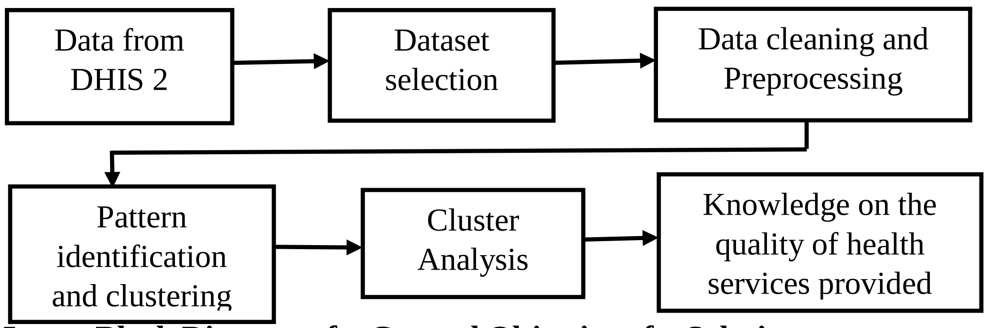

Figure 5: Block Diagram of a General Objective of a Solution

3.2.3 Phase III: Design and Development

An integrated quality measurement model for maternal, neonatal and child health services is the new technology product that this study proposed and developed. The standard cross-industry process for data mining (CRISP-DM) framework was adopted to carry out the experiment. The experiment was carried out in five phases as proposed in the CRISP-DM framework: Problem understanding, data acquisition, data preparation, model development and evaluation. All experimental steps were performed in python language using the scikit-learn library. The Scikit-learn library is an open machine learning library featuring various classification, regression and clustering algorithms used in solving machine learning problems. More details on the experiment are provided under the subsections below. This section has been further divided into subsections to adhere to the CRISP-DM framework as shown in Fig. 6.

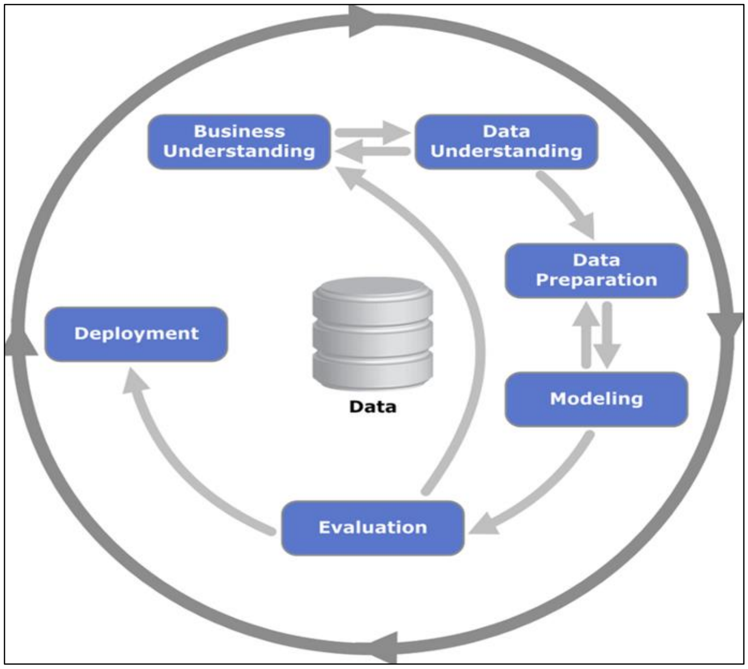

Figure 6: Cross Industry Process for Data Mining Framework (**Bošnjak *et al.*, 2009**)

(i) Business Understanding

The first step in the CRISP-DM model requires a clear understanding of the problem for which a solution is developed. The main objective of this study was to develop an integrated quality assessment model for maternal, neonatal and child health services. The Quality measurement model is considered an effective approach to quality measurement, a solution to the challenges seen in the existing quality measurement approaches. Also, the literature revealed the need for an effective and automated quality measurement approach in line with other ICT-based systems and applications currently in use. A machine learning-based model for quality measurement in MNCH care was proposed and developed. Consequently, the problem was considered an unsupervised machine learning problem. Clustering algorithms are employed in developing a model for quality measurement.

Clustering is a powerful technique for identifying data with similar characteristics, describing the hidden structures from unlabeled data and thus holds the potential to provide insight into the quality of MNCH services provided to pregnant women and children from the data collected from routine health services provided at health facilities. However, not all clustering algorithms yield the same performance or the same clusters. The study performed a theoretical comparison of the clustering algorithm to select the more suitable algorithm for the problem at hand. The comparison is based on the dataset's size, the number of clusters, and the dataset type (Mahmoud & Abbas, 2017; Mouton *et al.*, 2020; Sehgal & Garg, 2014; Wilkin & Huang, 2008). The four most popular clustering algorithms namely: K-means, Hierarchical, Self-organizing Map (SOM) and Expectation Maximization (EM), were theoretically compared.

For each factor, a literature search was conducted to establish the performance of each algorithm. Table 3 presents the analyzed results of the performance of clustering algorithms. Generally, all clustering algorithm has similar performance in clustering. From the analysis, K-means was selected based on its general performance, the clustering quality it has when the huge dataset is used, and it is resilient in the number of clusters needed.

Table 3: Performance of Clustering Algorithm

Sn	Algorithm	Criteria	Conclusion Obtained
1.	K-means	General Performance	Generally it has better performance
		Size of the dataset	• Its quality become very good when using huge dataset • For the sake of partitioning, it is recommended for huge dataset
		Number of clusters	Not specified
		Type of the dataset	• It has some ambiguity in some (noisy) data when clustered • Does not give better results when using random dataset
2.	Self-Organizing Map (SOM)	General Performance	Generally it has better performance
		Size of the dataset	Show good results when using small dataset
		Number of clusters	It has lower performance as k becomes greater
		Type of the dataset	• Give better results when using random dataset • Not more sensitive for noisy dataset • It have some ambiguity in some (noisy) data when clustered
3.	Hierarchical	General Performance	Generally it has better performance
		Size of the dataset	Show good results when using small dataset.
		Number of clusters	As the value of k becomes greater, the accuracy becomes better
		Type of the dataset	• It is more sensitive for noisy dataset • It have some ambiguity in some (noisy) data when clustered • Give better results when using random dataset
4.	Expectation Maximizing (EM)	General Performance	Generally it has better performance
		Size of the dataset	• Its quality became very good when using huge dataset • Recommended for huge dataset
		Number of clusters	Not specified
		Type of the dataset	• It have some ambiguity in some (noisy) data when clustered • Give poor results when using random dataset

(iii) Data Understanding

This phase comprises the first data acquisition step, and then the dataset description for a better understanding of the dataset acquired. Data used in this study was obtained from the District Health Information System (DHIS 2). The DHIS 2 is currently used as a centralized database and national health information system in several developing countries, Tanzania inclusive (Karuri *et al.,* 2014). Routine health data collected from the health facilities are stored in this data warehouse. Currently, data from DHIS 2 are used to facilitate analysis of health services, forecast required services, evaluate health workers' performance and support future health planning (Dehnavieh *et al.,* 2018; Kiberu *et al.,* 2014). It guarantees the availability of high-quality data to facilitate quality measurement as intended in this study. Five years maternal, neonatal and child health routine data collected monthly from all districts in Tanzania were congregated to form a dataset.

(iv) Data Preparation

Data is often incomplete and inconsistent and is more likely to contain many errors if not thoroughly checked. Data preparation was performed to clean the dataset, and a selection of indicators was performed to produce a more robust dataset for other machine learning experiments.

Data Pre-processing Missing Values Analysis

Data incompleteness and missing values in data records have been the major problem in health data. Data loss during the transfer from log books to databases, improper entries in the database, users' options not to fill some fields while entering data and forgetting to fill in some fields are among the reasons for missing values and poor data quality. Poor data quality affects the suitability of such data for different tasks if not further processed. Missing value analysis was performed to determine the missing values in the dataset used in this study. Due to the study's sensitivity, missing values have been appropriately handled to avoid inaccurate inferences about the data and expected results. Columns and rows with more than fifty per cent (50%) missing values were deleted. At the same time, the remaining missing values were imputed with the mean value of the column. Mean imputation was selected because it is the most naive imputation method and does not require any information about an observation to estimate a value.

Outlier Analysis

Outlier analysis was performed to identify the outliers that exist in the dataset. An outlier is a data observation that is distant from other observations. Outliers can affect results and assumptions; noting their presence is worth before deciding their inclusion or exclusion from the dataset during the experiment stage. Outliers can be identified using several statistical methods comprising visual and mathematical methods. The mathematical method, the Z-score method, was used to perform the multi-variety outlier detection. Outlier positions were identified, and the referred outliers were deleted to avoid their impacts on the final results.

Descriptive Analysis

Descriptive analysis is a data analysis method used to describe the basic features of the dataset. Descriptive analysis was performed to determine the central tendency of the dataset, which facilitated a better understanding of the dataset features.

Correlation Matrix

A correlation matrix was used to discover the degree to which variables depend on each other in the dataset. The correlation matrix defines variable correlations within the dataset. It often summarizes the strength and direction of the linear association between the variables. This information supported better preparation of the dataset to meet the expectations of the machine learning algorithm to be used.

Data type Identification

A data type check was performed to identify the dataset's data type. The type and way data are arranged can affect further operations in the dataset. This dataset has two types of data: Object and float. The object is the most general data type commonly assigned to columns with mixed types. The float type is assigned to numeric characters with decimals also columns with missing values in case the missing values have decimals. Period name and Organization unit name columns contain object type data, while the rest of the dataset columns contain float type data.

Dropping Irrelevant and Duplicate Columns

Columns that contain irrelevant data for quality measurement and those which contain information which may reveal the identity of the health facility were removed. Therefore, the columns with information such as "X_CH Watoto waliopatiwa hati punguzo ya chandarua', 'ANC HIV Prevalence under 20 years, 'ANC HIV prevalence (15-24 years)', 'Delivery Abnormal <20 yrs rate (C/S,, breech, vacuum)', 'Total Deliveries Children (Singlet and Twins)', 'Proportion of women delivered who are less than 20 years,' Percentage of pregnant women with known HIV status, 'ANC Proportion of pregnant women receiving ITN Voucher', 'ANC Positive women receiving Doses', 'X CH_Weight for Age (Miezi 9, 60% - 3SD)', 'period name', 'organisation unit name', 'Jumla Hudhurio la Kwanza"' were removed. In a dataset, a duplicate can be either row or column that appears more than once or rows and columns that bear different names but contain the same data. Duplicate rows and columns were removed to avoid disturbance. Columns with names that are difficult to read and written in abbreviations were also renamed to improve the readability of the dataset.

Indicator (Feature) Selection

Indicator selection, commonly known as feature selection in other machine learning problems, is a process of selecting the indicators in a dataset that contribute much to the prediction variable or output of interest (Guyon, 2015; Jovi *et al.*, 2015). Apart from informing relevant indicators that have to be included for better model performance, indicator selection helps in reducing model overfitting by removing redundant data in a dataset, improving accuracy by removing irrelevant features in a dataset, and minimising training time because reducing features in the dataset reduces the size of the dataset. In this study, feature selection was performed to identify and establish a set of MNCH indicators that significantly contribute to the quality of MNCH services. Indicator selection was made to select the quality indicators significantly contributing to quality measurement.

The indicator selection experiment was done using a random forest algorithm. The random forest algorithm offers a perfect feature selection indicator that shows each feature's relative importance or contribution to a prediction class. The random forest automatically calculates the relevance score of each feature in the training phase using Gini importance, also referred to as the total decrease in node impurity. The tree-based strategies used by random forests naturally rank the trees by how well they improve the purity of the node. By doing so, Gini impurity, a process of decreasing impurity in all trees, is done. During impurity decrease, the nodes with the most significant decrease in impurity appear at the start of the tree, while nodes with the slightest decrease in impurity appear at the end of the tree. After pruning the trees below a particular node, a new subset of features is created. The subset contains the features with a more significant contribution to the output of interest. This accurate, generalizable and interpretable process was used in this study to select the quality indicators for quality assessment in MNCH.

Further identification of essential indicators for quality measurement was accomplished by using a random forest classifier and two variables, namely the Gini importance index and permutation importance index. The first variable is obtained by adding up the weight of impurity decrease for all nodes when an indicator is used, and then it is averaged over all the trees in the forest. Therefore, to obtain the important indicator (X) for measuring quality (Y), a random forest classifier adds up the weight impurity decrease of other indicators (Xs) when the indicator (X) is used, and then it is averaged over all indicators available. This provides the list of essential indicators (X) for quality measurement (Y).

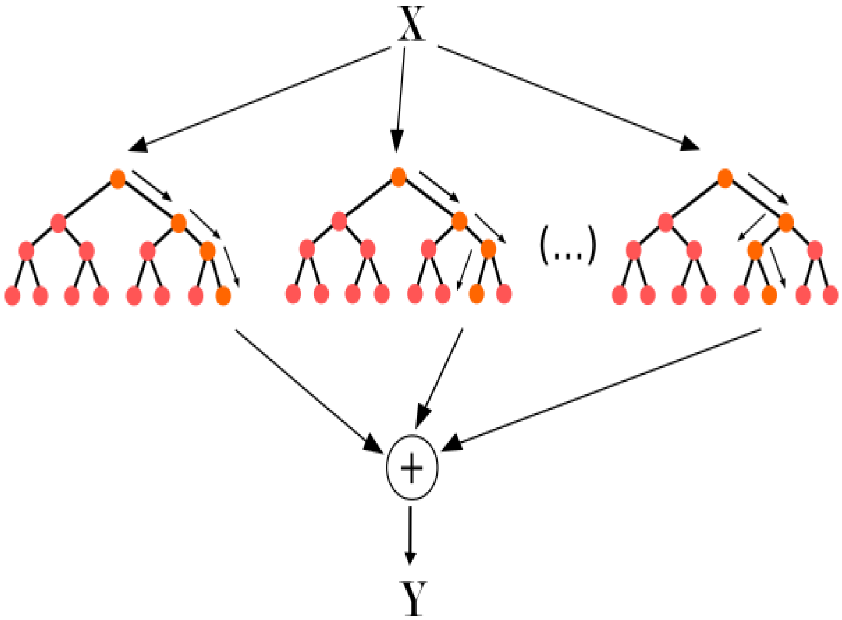

Figure 7: Random Forest Important Feature Selection with Impurity Decrease (Nembrini *et al.*, 2018)

(v) Modeling

The data preparation phase produced a clean and robust dataset for modelling (model development was done in python language using the scikit-learn library. In the modelling phase, all model development processes were accomplished to obtain a clustering model that facilitates the achievement of the study's intended objective. As stated earlier, the problem was taken as an unsupervised machine learning problem. It was considered so because the study intended to discover the quality of health services provided at health facilities from the routine health data collected. The study deployed the K-means algorithm, one of the most popular flat clustering algorithms, to build a clustering model. The developed clustering model, replicating the K-means algorithm, was used to assign every data point to one of the K clusters, where K is the number of clusters to be formed. Figure 8 illustrates the general modelling procedure for developing the clustering model using the K-means algorithm.

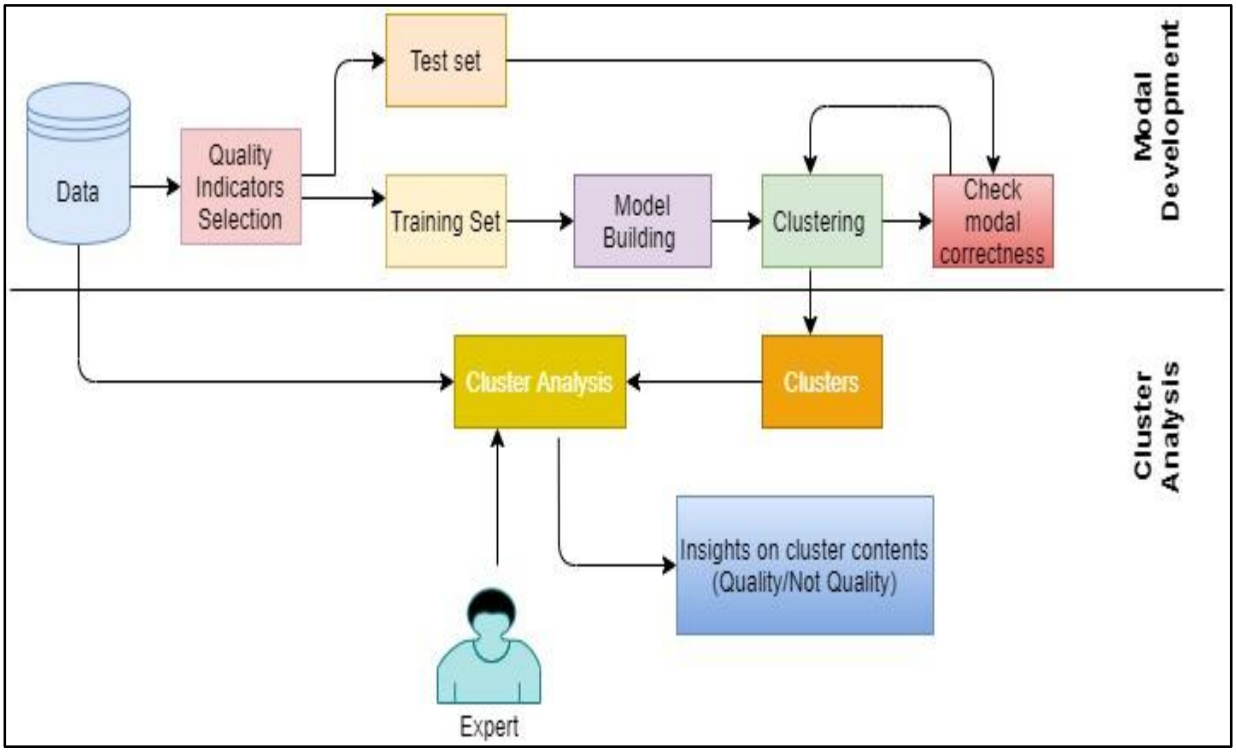

Figure 8: General Modeling Procedure

During modelling, the dataset was divided into the training set, which comprised 80% and the testing set, which comprised 20% of the whole dataset. Model development was done using the training set (80%). After obtaining a well-performing machine learning algorithm, then evaluation metrics to check the model correctness were performed using the remaining test set (20%). The Elbow method was used to identify the presence and the number of possible clusters within the dataset. The elbow appeared between numbers two and four (Fig. 9). These results established the fact that the dataset contains patterns (clusters) and a number of these clusters range from two clusters to four clusters.

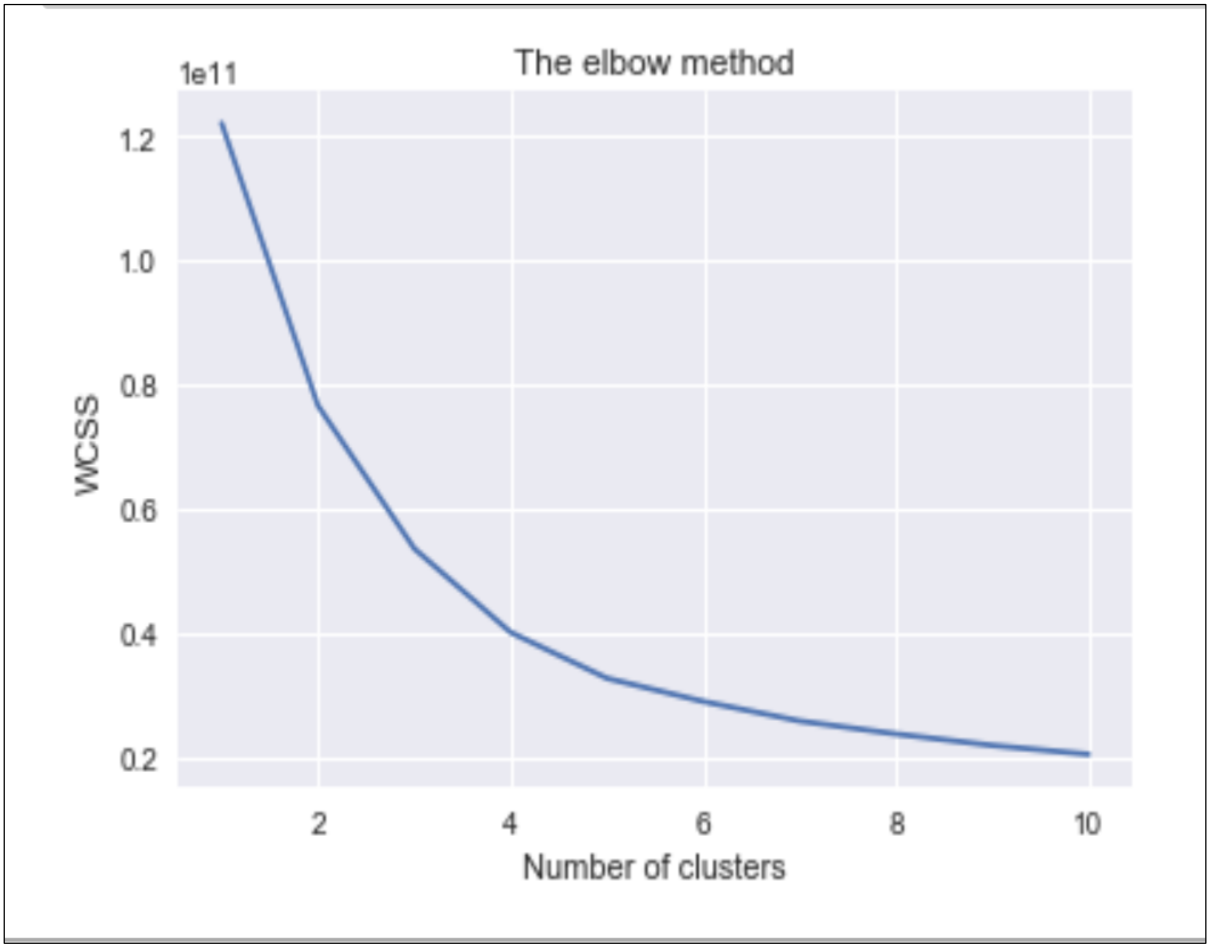

Figure 9: Elbow Method

The K-means algorithm normally begins by selecting K random seeds assumed to represent centres (centroid) of the K initial clusters. Using the elbow method, K = 2 was selected as the initial K value illustrated in Fig. 9. The algorithm then proceeds to compute each data point's distance (or similarity) from all the two K points. These distance values are used to assign every data point to one of the K clusters. A cluster in K-means is a sphere with the centroid at its centre of gravity. To form a cluster, K-means minimizes the average distance of data points from their cluster centre, defined as the mean or centroid of the data points in a cluster. The centroid of the data points in a cluster is computed as:

$$\mu(\omega) = \frac{i}{\omega} \sum_{x \varepsilon \omega} \vec{x} \tag{1}$$

Where:

μ = Centroid

ω = Cluster

i = number of iterations

K = Number of clusters

A data-point is assigned to a cluster closest to it, or in other words, to the cluster whose centroid has the smallest distance from the data-point out of all such K centroids. Once all data points are assigned to one of the K clusters, all the K clusters' centroids are recomputed. After that, the process is iterated with the new centroids as new cluster centres. This iterative process is repeated until no new cluster assignment is done. As a terminating criterion, the residual sum of squares (RSS), a squared distance of each data-point vector and its cluster centroid were summed over all vectors.

(vi) Evaluation

At this stage, model evaluation was accomplished to check the model correctness in assigning the data points into their respective clusters. Model correctness was checked using the residual sum of squares (RSS) and purity.

Residual Sum of Squares

The objective of clustering algorithms is to achieve high intracluster similarity (similar data points within a cluster) and low intercluster similarity (different data points from different clusters). It is often viewed as an internal criterion of clustering quality. The residual sum of squares (RSS), defined as the squared distance of each vector from its centroid summed over all vectors, is a measure of this internal criterion. A good score of RSS (internal criterion) is a good representation of clustering quality. The RSS is computed by:

$$RSS = \sum_{K=1}^{K} RSS \tag{2}$$

Where

$$RSS_K = \sum_{x \epsilon \omega_K} \left| \vec{x} - \mu(\omega_{K)} \right| \tag{3}$$

Purity

High scores in internal criterion measures do not always turn out to be an accurate and effective measure of clustering quality. This study, therefore, deployed an alternative evaluation which is the external criterion of the clustering results, to evaluate clustering quality. Purity is one widespread external criterion used to evaluate the clustering quality directly. Each cluster is assigned to the class which is the most frequent cluster. Then the accuracy of each assignment is measured by counting the number of correctly assigned data points, dividing by the total number of data points. Purity is then calculated by evaluating how many data points are assigned to the correct class using the formula below:

$$Purity\ (\Omega, C) = \frac{1}{N} \sum_{K} max_j \left| \omega_k \cap C_j \right| \tag{4}$$

Where, Ω = {w1, w2… wk} is the set of clusters and C = {c1, c2… cj} is the set of classes. Here wk denotes the set of data points in the cluster wk, and CJ denotes the set of data points in the class CJ. Bad clustering has purity close to '0', and a perfect clustering has a purity value of '1'.

(vii) Model Deployment

Model deployment is taking the trained machine learning model and making its results available to users or other systems. The developed machine learning-based approach for quality assessment will only bring meaning if the information provided by the model on the quality of MNCH services will be made available to users for whom it was developed. For model validation purposes, the results of this model were made available to reproductive and child health coordinators from the Kilimanjaro region.

3.2.4 Phase IV: Demonstration

The demonstration is the fourth phase in design science research methodology (DSRM), which requires using artefacts to solve one or more instances of the problem. However, due to a lack of avenues for a model demonstration to the public, this phase was implemented only to the targeted population of MNCH experts and stakeholders, including reproductive and child health coordinators. The experts and stakeholders underwent step-by-step experimental processes in which the model performed clustering and cluster analysis. The goal was to inform stakeholders in MNCH how the developed artefact can be used to measure the quality of MNCH services.

3.2.5 Phase V: Model Evaluation

Evaluation in design science research methodology (DSRM) requires observation and assessment of how well the artefact supports a solution to the problem. In this manner, evaluation should involve comparing the objectives of a solution to actual observed results from the use of the artefact in the demonstration. It is similar to model validation, the act of determining whether a model reasonably represents or approximates the actual system for its intended use. Model validation was accomplished in two stages: Conceptual and operational validation. This evaluation phase validation step was to transfer confidence in model performance to the MNCH experts and stakeholders' community. Thus, an important step was to engage this community representing the developed model's end users.

(i) Conceptual Validation

Commonly, conceptual validation consists of identifying and evaluating the model's undelaying theory and comparing the methodology of the model with that of alternative approaches. Conceptual validation resulted in a qualitative assessment of a model's theoretical underpinnings and its implantation to be evaluated in the light of sound and accepted theoretical methods. For this model, the focus of conceptual validation was on the comparison of the methodology of the model with the alternative approaches. The primary methods employed during conceptual validation were model survey and model walkthrough.

Model Survey

Without the experience and opinions of the MNCH experts and stakeholders' community, the new artefact will not be able to address the concerns of the end users. A survey questionnaire was prepared and distributed to MNCH experts and the stakeholders' community to collect their experience and opinions on the developed model.

Model Walkthrough

A model walkthrough involved a group of RCH coordinators and a few MNCH experts purposively sampled from maternal and child health (MCH) centres in Kilimanjaro region who carefully reviewed and revisited the model's logic and the basic structure of the model to establish the validity of the model on its specific uses. The experts were requested to validate the model by: (a) Comparing the artefact's functionality with the solution objectives, (b) Adherence of the artefact to the existing MNCH quality assessment criteria and national standards, and (c) The MNCH expert's acceptance.

(ii) Operational Validation

The procedures associated with operational validation are commonly designed to present a quantitative measurement of comparison between the newly developed approach and the existing or alternative approaches. However, since there was no standard quality measurement approach constantly used for MNCH quality measurement in Tanzania to establish a comparison, the operation validation was supposed to be performed by comparing the quality measurement model with a few quality measurement approaches used for MNCH quality measurement in Tanzania. The validation criteria chosen by MNCH experts were to reflect model performance based on the intended application of the model. Operational validation was accomplished in two phases. The first phase was; the identification of the performance validation criteria. A discussion was done with the MNCH experts on the best criteria to gauge the operational performance of the newly developed quality measurement model compared with existing quality measurement approaches.

In the first phase of operation validation, the group agreed to validate the performance of the developed quality measurement model by comparing its performance to other quality measurement approaches previously used for quality measurement. Four quality measurement approaches namely: (a) Service availability and readiness assessment (SARA), (b) Service delivery indicator (SDI), (c) Service provision assessment (SPA), and (d) Needs assessment for emergency obstetric and newborn care (EmONC), were selected to be used in the performance comparison. However, while selecting the performance criteria for comparison, the team found that the approaches are dissimilar to the quality measurement model to be compared. The team, therefore, evaluated the model's operational performance without comparison. Table 4 present the performance criteria selected for validation. It was agreed that the validating criteria chosen will reflect a quality measurement model based on the intended application.

The group further agreed that if the chosen criteria are valid, the quality measurement model will be valid for its intended application. Second, an operational test for the chosen performance criteria was performed. A wide array of statistical methods is available for the second phase of operational validation. However, there is no utterly definitive approach; therefore, the decision to choose a specific method is often based on the characteristics of the model and its intended use. In this section, the operational performance of the quality measurement model was compared to the operational performance of existing quality measurement approaches based on the selected performance criteria.

Table 4: Selected Performance Criteria for Validation

Criteria	Description
Usability	The ability of quality measurement model to fulfill its intended application
Suitability	The appropriateness of the quality measurement model in quality measurement
Efficient	Ability to work with few resources
Upgrade ability	Upgrading into newer versions depending on technology advancement.
Maintainability	Availability of developer support and continue to be in a working condition.
Interoperability	The ability of quality measurement model to be integrated and work with other systems available in health sector
Accessibility	The availability of quality measurement model when needed

3.2.7 Phase VI: Communication

Scholarly publications have been used in communication. Scholars have emphasized communication to inform researchers and other relevant audiences on the research problem and its importance, the artefact developed to address its utility and novelty, the rigour of its design, and its effectiveness. Three manuscripts have been prepared from the study to communicate the artefact to the researchers and other relevant audiences.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Results

In this Chapter, the study's results are presented and discussed regarding the study's general objective, which was to develop an integrated quality measurement modal for maternal, neonatal and child health services. The specific objectives of the study were: (a) To review quality measurement approaches currently used to measure quality in MNCH care in Tanzania, (b) To develop a quality measurement model for maternal, neonatal and child health services in Tanzania, and (c) To validate the effectiveness of machine learning based model in MNCH quality measurement.

4.1.1 Review of Approaches used for Quality Measurement in Maternal, Neonatal and Child Health

(i) Existing Maternal, Neonatal and Child Health Quality Measurement Approaches

The revised literature stressed the poor quality of MNCH services provided to pregnant women and children as an underline cause of high death occurrences. The literature further revealed that the death causes are much known, and the majority could be prevented if women and children had access to quality MNCH services. Therefore, the quality of MNCH is an underpinned factor in reducing maternal and neonatal deaths. Figure 10 illustrates the relationship between high death occurrences, poor MNCH services and ineffective MNCH quality measurement.

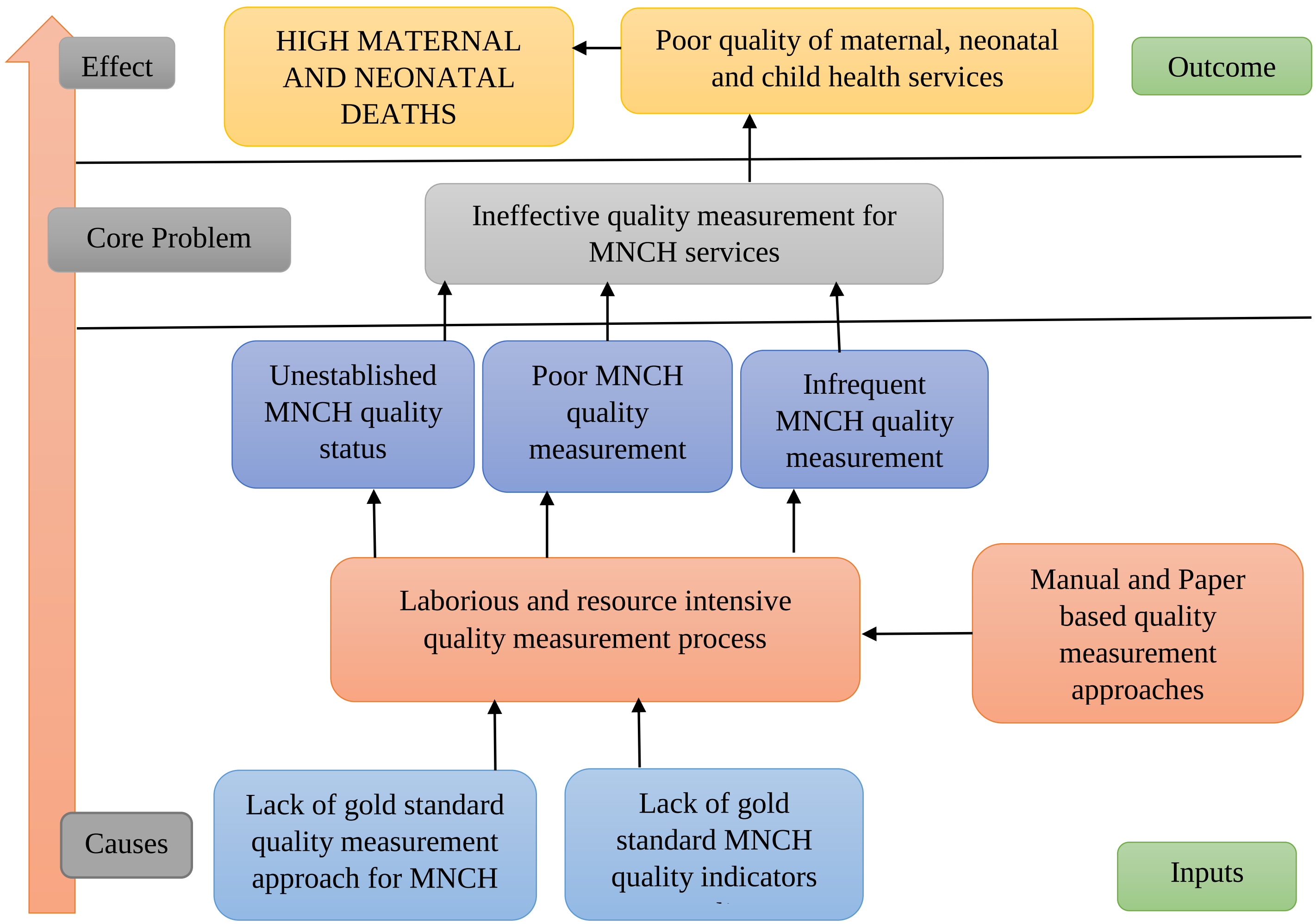

Figure 10: High Maternal and Neonatal Deaths: Cause and Effect Diagram

The literature review identified 18 quality measurement approaches used for quality measurement in developing countries. Among 18 quality measurement approaches, nine (9) approaches have been used for quality measurement in Tanzania. Studies by Kruk *et al.* (2016b), Hozumi *et al.* (2008) and Hanson *et al.* (2014) presented tailored quality measurement approaches which were used for quality measurement in Tanzania. Also, facility-based approaches namely: SARA, SPA, SDI and needs assessment for emergence obstetric care were reported to be used for MNCH quality measurement in Tanzania. It was further noted that most quality measurement approaches were developed to meet general quality measurement needs; very few approaches were explicitly developed for the country's requirements. Therefore, to enhance the quality measurement process and improve MNCH services. Tanzania needs a quality measurement approach with a specification tailored to suit its quality measurement needs. Nevertheless, the literature does not reveal the presence of a gold standard quality measurement approach universally accepted for MNCH quality measurement.

(ii) Limitations of Existing Quality Measurement Approaches

Analysis of quality measurement approaches revealed several limitations that bound the effectiveness of the available approaches in quality measurement. The analysis done in this study revealed that data sources and data collection mechanisms, indicators for quality measurement and expertise and quality measurement frequency are the major limitation to the effectiveness of existing approaches in MNCH quality measurement. Resource inefficiency portrayed by existing quality measurement approaches is highly contributed by high financial and human resources the approaches require during data collection, tools preparations, data collection and quality measurement exercise. It has been observed that most quality measurement approaches use data acquired from DHS and other surveys, direct clinical observation, medical records reviews, client exit interviews and service provider interviews, to mention a few. For example, the collection of data from direct clinical observation requires an expert who understands all the undergoing processes in a particular clinical procedure observed.

In the same way, data collection from the mentioned sources need a trained data collector. It has also been observed that some quality measurement approaches take up to several weeks to accomplish in multiple health facilities. Therefore, to accomplish quality measurement in a country requires a quality measurement team, including experts required, to prepare data collection tools, train data collectors, perform quality measurement exercises and prepare and disseminate quality assessment results for a couple of months. Therefore, the quality measurement process requires adequate financial and human resources. Given budgetary constraints and shortage in staff healthcare in developing countries and Tanzania inclusive, these limit the effectiveness of quality measurement approaches and quality measurement frequency.

4.1.2 Development of Maternal, Neonatal and Child Health Quality Measurement Model

(i) Important Indicators for Maternal, Neonatal and Child Health Quality Measurement

It has been observed that countries worldwide, especially in developing countries, have been relying on the World Health Organization (WHO) to recommend and provide guidelines and guidance on indicators to be used for quality measurement in MNCH. Based on WHO's guidelines and quality indicators recommendations, various quality indicators have been identified and developed by individuals, government agencies and other stakeholders in MNCH. For example, Dettrick *et al.* (2016) derived the quality indicators used in measuring the quality of maternal and newborn care in developing countries from the 2012 Indonesian Demographic and Health Survey data set. Tripathi *et al.* (2019) obtained the quantitative indicators for labour and delivery care quality measurement from the studies describing labour and delivery care quality indicators.

In 2014, Kenya took the initiative to validate and identify maternal health indicators that can practically be applied in health facilities and population-based health surveys to accurately evaluate national and global maternal health care in the country (Warren *et al.*, 2014).

Indicators for quality measurement have been developed/derived whenever the need for quality measurement arises; in 2012, WHO recommended 11 indicators for maternal and child health monitoring and evaluation (WHO, 2011). Later, in 2014, WHO came up with another set of indicators for global measurement and reporting on the quality of care provided for maternal, newborns and children at health facilities that should be used to evaluate Millennium Development Goals (MDG) (WHO, 2014).

Furthermore, the study found that critical analysis done by several scholars on broad sets of quality indicators available in the literature for MNCH quality measurement showed that most indicators are not readily suitable for adaptation and implementation (Saturno-hernández *et al.,* 2019). The literature further reveals that only a few published indicators comply with the requirement of empirically tested scientific validity, usefulness and feasibility. It was also found that neither WHO nor individuals, government agencies and other MNCH stakeholders maintain a finite set of quality indicators that can fit all quality measurement contexts.

This study, therefore, established a set of most important indicators for quality measurement in MNCH. Random Forest (RF) classifier was used to accomplish the task. The process was illustrated in Section 3.2.3 of this study. The quality indicators were used to develop quality measurement model (clustering model). The identified a list of important quality indicators for MNCH quality measurement and machine learning based quality measurement model are essential input in effective quality measurement process. Figure 11 illustrate the role of effective quality measurement approach in MNCH quality improvement hence reduction of maternal and neonatal deaths. From the experiment, 29 indicators shown in Fig. 12, were identified as essential indicators for quality measurement in MNCH. Of 29 important indicators, eight indicators marked with bold text and asterisk in Table 4 are considered the most important quality indicators for MNCH quality measurement. The Table 5 provides more details on the selected quality indicators.

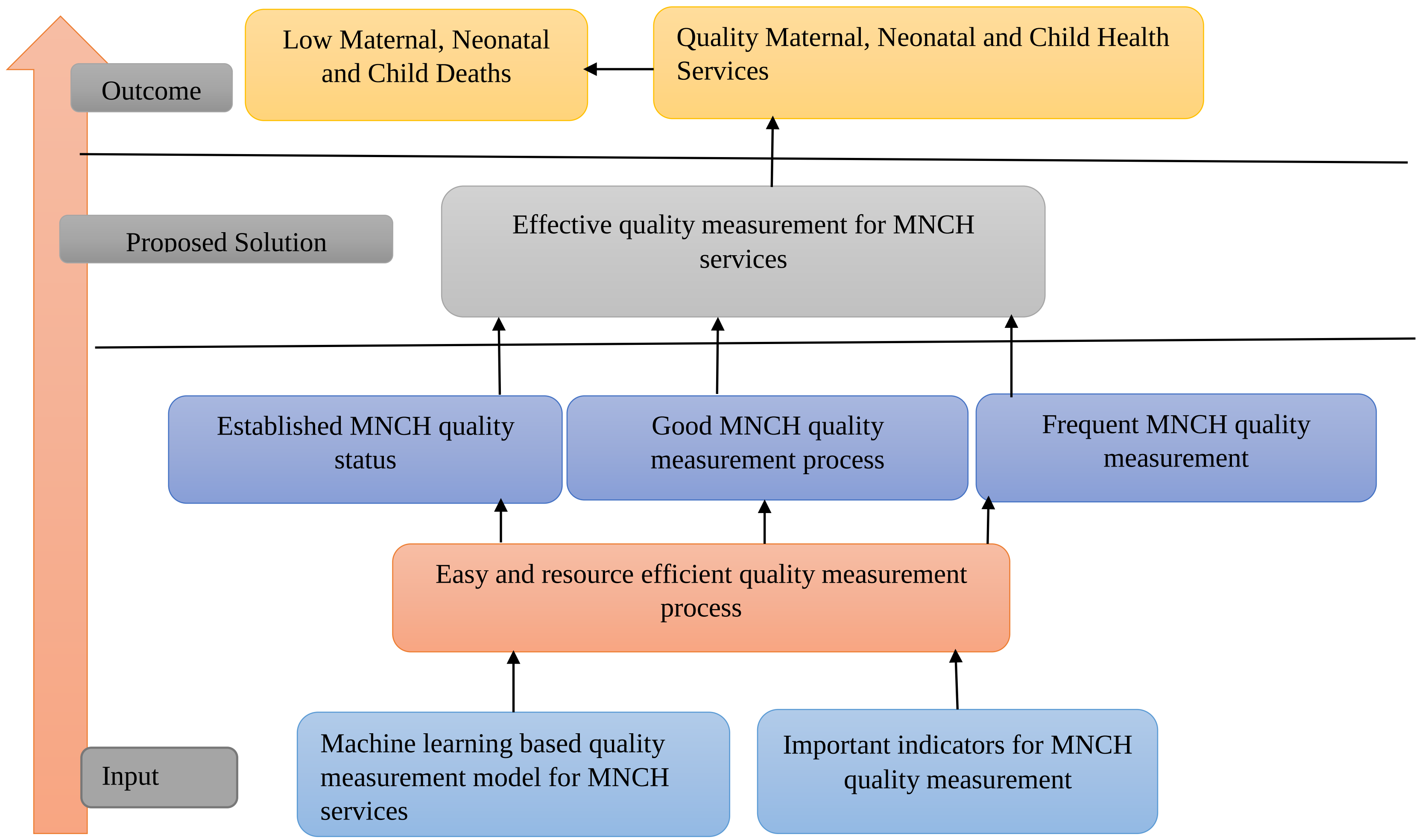

Figure 11: High Maternal, Neonatal and Child Deaths – Proposed Solution Diagram

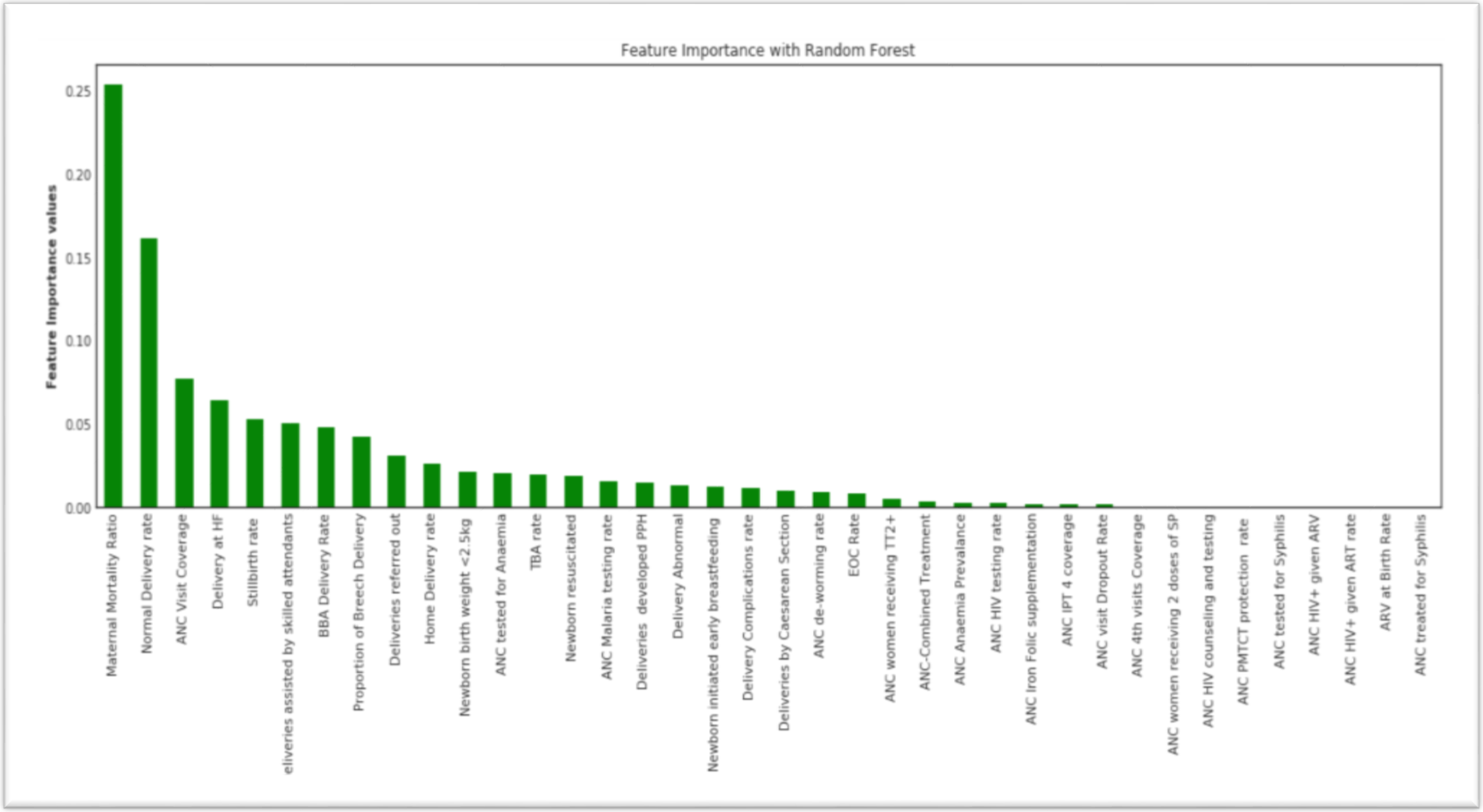

Figure 12: Important Indicators with Random Forest

Table 5: Summary of Selected Important Quality Indicators (features) for Quality Measurement

Indicator	Meaning	Phase in Continuum Care	Information Covered
***Maternal Mortality Ratio (MMR)**	Maternal mortality refers to deaths due to complications from pregnancy or childbirth	Pregnancy and Childbirth	The ratio of women deaths due to maternal complications
***Still-birth rate**	Stillbirth refers to the loss of a baby before or during delivery	Pregnancy and Childbirth	Rate of babies lost before or during pregnancy
***Delivery at the health facility**	Deliveries that occur at the health facility	Childbirth	Number of deliveries at health facilities
***Deliveries assisted with skilled attendants**	Deliveries that are assisted by skilled birth attendants or midwife	Childbirth	Number of births attended by skilled birth attendants
***Normal delivery rate**	Deliveries by vagina	Childbirth	Rate of women who gave birth through the vagina
***Born before arrival rate**	Born before arrival refers to the childbirth that occurs outside the health facility	Childbirth	Rate of deliveries occurred outside the health facility or on the way to the health facility
***Antenatal care visit (ANC) coverage**	Coverage of antenatal care with the communities. Antenatal care visit coverage is the care provided for the mother during pregnancy to improve the health of the mother and unborn baby	Pregnancy and Childbirth	Coverage of antenatal care
***Proportional of breech delivery**	Breach delivery refers to the baby who is born bottom first instead of head first	Pregnancy and Childbirth	Number of babies born bottom first in total births occurred in a specified area

Indicator	Meaning	Phase in Continuum Care	Information Covered
Deliveries referred out	Women who referred to deliver in tertiary hospitals	Pregnancy and Childbirth	Number of women who are referred to tertiary hospitals
Home delivery rate	Home delivery refers to deliveries occur at home	Pregnancy and Childbirth	Rate of women who gave birth at home
Newborn birth weight less than 2.5 kilogram	Newborns who weigh less than 2.5 kilograms at birth	Pregnancy and Childbirth	Number of newborns with birth weight less than 2.5 kilograms
Antenatal care visits (ANC) tested for anaemia	Antenatal care visit when anaemia is tested	Pregnancy	Number of women who are tested for anaemia during ANC visits
Traditional birth attendant (TBA) rate	Traditional Birth Attendants refers to the deliveries attended by traditional birth attendants	Pregnancy and Childbirth	Rate of births attended by traditional birth attendants
Newborns Resurrected	Newborn resuscitation is intervention done to help the newborn to initiate breathe and heartbeat	Childbirth	Number of newborns-initiated breaths and heartbeat
Antenatal care visit (ANC) malaria testing rate	Antenatal care visit when malaria is tested	Pregnancy	Rate of women who are tested for malaria during ANC visits
Deliveries developed Postpartum hemorrhage (PPH)	PPH is defined as "blood loss of more than 500 mL following a vaginal delivery or more than 1000 mL following cesarean delivery"	Childbirth	Number of women developed PPH during delivery
Indicator	**Meaning**	**Phase in continuum care**	**Information covered**

Indicator	Meaning	Phase in Continuum Care	Information Covered
Delivery abnormal	Delivery abnormal refers to "the position a born baby is facing. The position is facing forward, and abnormal presentations include face, brow, breech, and shoulder"	Childbirth	Number of abnormal deliveries
Newborn initiated early breastfeeding	Early initiation of breastfeeding referred to the "provision of mother's breast milk to infants within one hour of birth and ensures that the infant receives the colostrum or "first milk"	Pregnancy and Childbirth	Number of newborns initiated early breastfeeding
Delivery complication rate	Refers to the complications associated with childbirth such as blood loss, wound infection, cystitis, endometritis, hematoma, and reoperation	Childbirth	Rate of woman who had delivery complications
Deliveries by caesarian section	A cesarean delivery also known as a C-section or cesarean section is the surgical delivery of a baby. It involves one incision in the mother's abdomen and another in the uterus	Childbirth	Number of women who deliver by C-section
Antenatal care visit (ANC) deworming rate	Antenatal care visit when a pregnant woman is given deworming tablets	Pregnancy	Rate of women received deworming tabs during ANC visit
Antenatal care visit (ANC) women receiving more than two tetanus vaccination (TT2+)	Antenatal care visit when a woman received more than two tetanus vaccination	Pregnancy	Number of women received more than two tetanus vaccination during ANC visit

Indicator	Meaning	Phase in Continuum Care	Information Covered
Antenatal care visit (ANC) combination treatment	Antenatal care visit when a woman receiving combination treatment	Pregnancy	Number of women received a combination treatment during ANC visits
Antenatal care visit (ANC) anaemia prevalence	Antenatal care visit when anaemia is tested	Pregnancy	Number of women tested for anaemia prevalence
Antenatal care visit (ANC) human immunodeficiency virus (HIV) testing rate	Antenatal care visit when human immunodeficiency virus (HIV) is tested	Pregnancy	Rate of women tested for human immunodeficiency virus (HIV) during ANC visit
Antenatal care visit (ANC) iron-folic supplementation	Antenatal care visit when a woman receiving iron-folic supplementation	Pregnancy	Number of women received folic supplementation during ANC visit
Antenatal care visit (ANC) intermittent preventive treatment in pregnancy (IPTP) 4 coverage	Antenatal care visit when a woman receiving intermittent preventive treatment in pregnancy (IPTP) 4	Pregnancy	Number of women received intermittent preventive treatment in pregnancy (IPTP) 4 during ANC visit
Antenatal care visit (ANC) dropout rate.	Antenatal care visit when anaemia is tested	Pregnancy	Rate of woman stop visiting antenatal care

4.1.3 Model Development

(i) Clustering Results

The study intended to use maternal and child health data collected from routine health services to measure the quality of health services provided. K-means algorithm was used to develop a clustering model. Clustering was performed to group a dataset into homogeneous and distinct clusters. Figure 10, 11, 12 and 13 present the clustering results obtained.

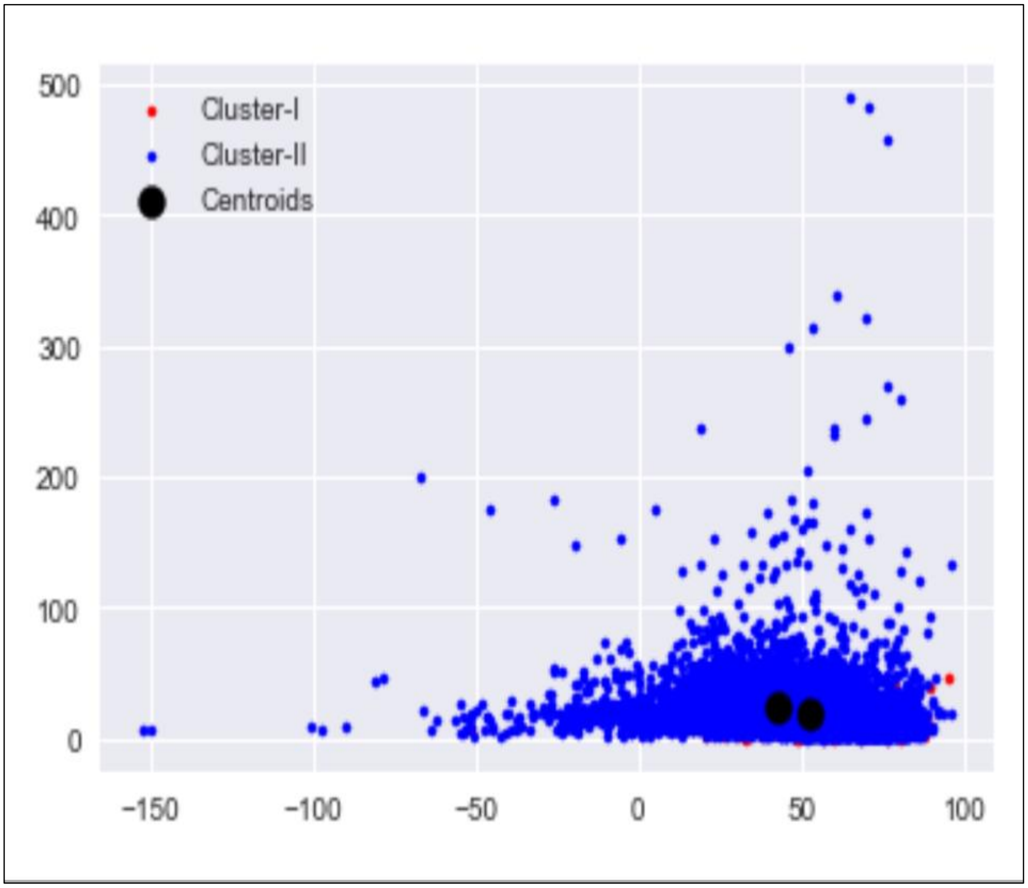

Figure 13: 1st iteration

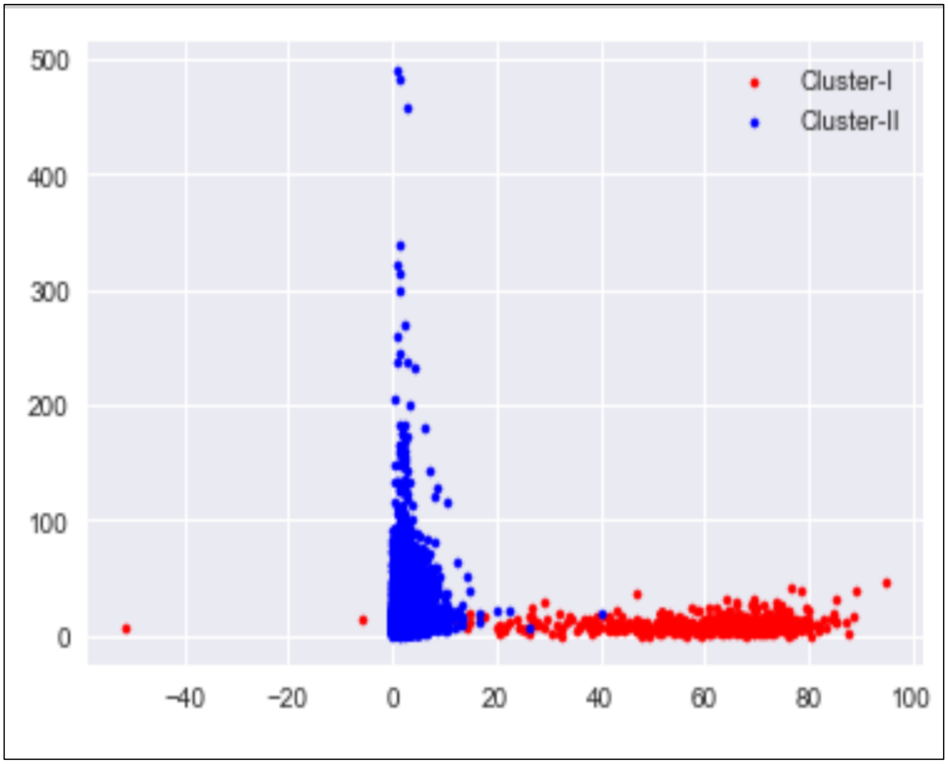

Figure 14: **2nd iteration**

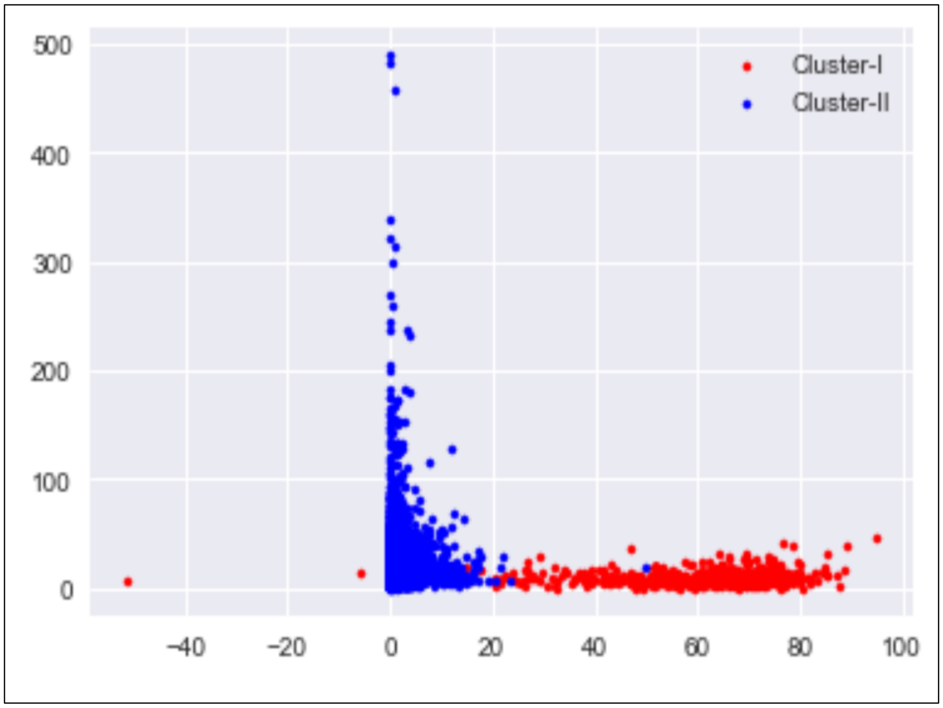

Figure 15: **3rd iteration**

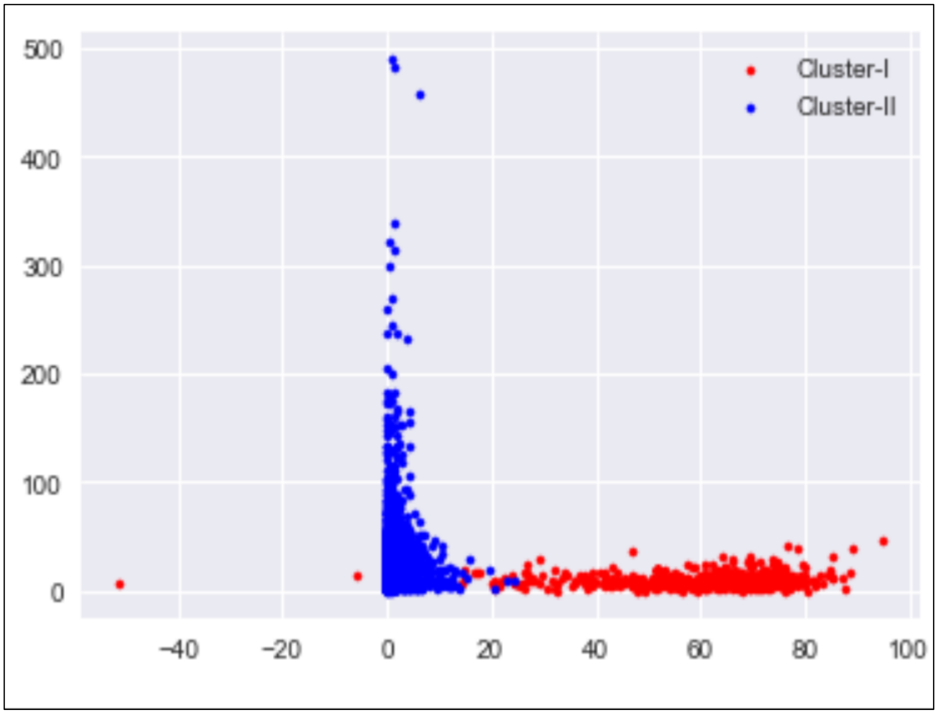

Figure 16: 4th iteration

(ii) Cluster Analysis Results

Clustering is widely used in a variety of statistical and machine learning applications. These applications can be roughly divided into two objectives. The first objective is the identification of homogeneous groups within a dataset, and the second one is a summarization of a dataset into representative points or cluster prototypes. Objective one spans a broad range of real-world problems, including the discovery of gene groups with similar functions and the identification of communities in social networks. This study used clustering to discover data points with similar characteristics. As demonstrated in Subsection 4.1.3 (i) of this study, the data points in the dataset were successfully grouped into two clusters. Similarly, the second clustering objective covers many essential problems in the current big data era, including data summarization and data comprehension. This section focuses on the latter objective, data comprehension, representing a dataset by its prototypes.

For easy knowledge discovery, cluster members in each cluster were labelled. The data points in the first cluster were labelled by "0", and those in the second cluster were labelled by "1". Using the quality indicators illustrated in Table 6, MNCH experts rated each data record by giving a "good quality" score denoted by "1" or "poor quality" score denoted by "0" the labels that guided knowledge discovery from each cluster. The new labels were appended to the dataset with column names "Pred" for cluster identification label and "Expert Judgment". These two columns, "Pred" and "Expert judgment", have enabled the discovery of the cluster that contains data records that show high-quality health services and those that show poor-quality health services. It was found that the first cluster denoted by “0” contains data records that depict high-quality MNCH services, and the second group denoted by “1” contain data records that depict poor-quality MNCH services. However, few data records belong in the first cluster (“0”) but contain data records that depict poor quality. Figure 14 and 15 show the dataset head and tail that illustrate the cluster analysis results.

Table 6: Quality Indicators used to Guide Expert Judgment

Quality indicator	Description
Antenatal care visits (ANC)	Percentage of women with a live birth in a given time period who received antenatal care, four times or more times from any provider (Indicators, 2018; WHO, 2016a)
Facility delivery	Proportion of women who gave birth in a health institution (number of deliveries in institutions among total deliveries)
Skilled birth attendance	Percentage of live births attended by skilled health personnel during a specified time period
Stillbirth	Baby born with no signs of life after a specified threshold (Indicators, 2018)
Maternal mortality	Death of a woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration and the site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management, but not from accidental or incidental causes (Indicators, 2018)
Neonatal mortality	A death that occurs during the neonatal period; the first 28 days of life (WHO, 2016b)
Post-partum care coverage	Percentage of women who have post-partum contact with a health provider within two days of delivery (Indicators, 2018;WHO, 2016a)
Newborns receiving essential newborn care	Percentage of newborns who received all four elements of essential newborn care such as immediate and thorough drying, immediate skin-to-skin contact, delayed cord clamping and initiation of breastfeeding in the first hour (Indicators, 2018)

```
In [38]: testset.head()
```

Out[38]:

ANC HIV evalence (15-24 years)	ANC HIV prevalence 1st Test	ANC HIV prevalence 2nd Test	ANC HIV testing rate	...	Proportion of deliveries referred out	Proportion of new born alive with birth weight <2.5kg	Proportion of newborn initiated early breastfeeding	Proportion of newborn resuscitated	Proportion of women delivered at health facility	Proportion of women delivered who are less than 20 years	Still birth rate	TBA Delivery rate	pred	Expert Judgment
2.678925	1.300000	0.160000	97.500000	...	0.420000	7.500000	92.800000	2.800000	97.60000	23.200000	0.360000	0.740000	0	1
2.678925	1.600000	0.230000	97.300000	...	0.090000	3.400000	97.000000	8.100000	98.40000	20.300000	1.500000	0.110000	0	1
2.678925	2.013897	3.094317	91.245312	...	2.232117	5.802506	85.457236	9.596289	90.70771	20.395394	1.374436	1.768584	0	0
2.678925	2.013897	3.094317	91.245312	...	2.232117	5.802506	85.457236	9.596289	90.70771	20.395394	1.374436	1.768584	0	0
0.000000	3.100000	0.000000	37.800000	...	1.400000	0.000000	100.000000	10.100000	97.20000	12.700000	3.000000	1.768584	0	1

Figure 17: Test set head

In [45]:
```
testset.tail()
```

Out[45]:

HIV nce 20 ars	ANC HIV prevalence (15-24 years)	ANC HIV prevalence 1st Test	ANC HIV prevalence 2nd Test	ANC HIV testing rate	...	Proportion of deliveries referred out	Proportion of new born alive with birth weight <2.5kg	Proportion of newborn initiated early breastfeeding	Proportion of newborn resuscitated	Proportion of women delivered at health facility	Proportion of women delivered who are less than 20 years	Still birth rate	TBA Delivery rate	pred	Expert Judgment
.85	52.678925	0.25	0.0	101.2	...	0.54	3.3	62.5	9.2	97.7	15.7	0.42	0.71	0	1
.70	52.678925	2.60	0.0	101.7	...	0.96	1.5	99.0	10.8	93.3	20.7	1.50	0.45	0	1
.00	52.678925	1.10	0.0	95.4	...	0.00	7.6	78.4	19.4	97.6	14.7	2.90	0.49	0	1
.80	52.678925	1.50	0.0	97.0	...	0.00	6.8	79.8	16.6	97.7	15.6	0.60	0.94	0	1
.76	52.678925	2.10	0.0	97.6	...	0.39	6.0	85.1	7.8	99.3	11.6	3.40	0.00	0	1

Figure 18: Test set Tail

4.1.4 Model Evaluation

This section presents the results of the model evaluation (evaluation report).

(i) Conceptual Validation

Model Survey Results

Survey questionnaire (Appendix 1), was distributed to various MNCH stakeholders and health personnel to collect experience and opinions on the quality measurement model. Some of the critical comments are summarized in Table 7.

Table 7: Survey Questioner Results

S/n	Survey question	Key comment(s)
1	How well can you describe the demonstrated approach for quality measurement?	Good quality measurement approach
2	How well does the demonstrated approach meet quality measurement needs?	The approach meet quality measurement needs
3	What are the strength of the demonstrated approach in quality measurement?	It uses advanced technologies and it is cost efficient
4	What are the weaknesses of the demonstrated approach in quality measurement?	• The approach does not show the technicalities it uses to measure the quality from routine health data. • If not, an ICT personnel you cannot understand what is going on until you see the results
5	What is/are important things/features that you think the approach is missing	No response
6	What would you like to change in the quality measurement model	No response
7	How easy is it to use quality measurement model for quality measurement	It is easy
8	Were you able to understand the quality measurement results	Yes
9	Compared to existing quality measurement approaches; how do quality measurement model perform	Good
10	Why would you choose quality measurement model over the traditional quality measurement approaches	• It is easy and convenient to use • It is effective in quality measurement • It is resourceful in quality measurement
11	To what extent do you agree with the following statement “the quality measurement model is effective in MNCH quality measurement”	All respondents agreed to the statement “the quality measurement model is effective in MNCH quality measurement”
12	On a scale of 0 to 10 how likely are you to recommend the quality measurement model for quality measurement in Tanzania	All respondents recommended the quality measurement model quality measurement in Tanzania
13	What will you say to someone who ask about quality measurement model	It is an excellent approach for quality measurement in Tanzania

Model Walkthrough Results

The model walkthrough was intended to validate the model against its intended use. A group of reproductive and child health coordinators (RCH-Co) from five districts in Kilimanjaro region was gathered to review the model's logic and basic structure to establish the model's validity in its intended use. The review was mainly based on comparing the artefact's functionality with the solution objectives, adherence of the artefact to the existing MNCH quality assessment criteria and national standards. Lastly, each expert was requested to provide his/her acceptance remarks on the suitability of the approach in MNCH quality measurement. Table 8 illustrate model walkthrough results.

Table 8: Model Walkthrough Results

Review Criteria	Agreed Observations
Comparison of quality measurement model's functionality to with the solution objective	Clustering and cluster analysis results have proven that artifact's functionally matched the solution objectives. The knowledge discovered in first cluster indicated the services provided had good quality and second cluster indicated services provided had poor quality.
Adherence of the quality measurement model to the existing MNCH quality measurement criteria and national standards	The model did not adhere to any existing quality measurement criteria, also it does not explicitly comply with national standards for quality measurement during quality measurement process. However, the quality measurement results were correct. In all circumstances that signified poor quality of services by traditional methods the results by quality measurement model showed poor quality as well and the same to good quality circumstances.
Expert's acceptance remarks	It is performing well

(ii) Operational Validation Results

Operational validation was carried out with a group of RCH coordinators and a few MNCH experts purposively sampled from the Kilimanjaro region maternal and child health (MCH) centres. Figure 16 presents the operational validation results.

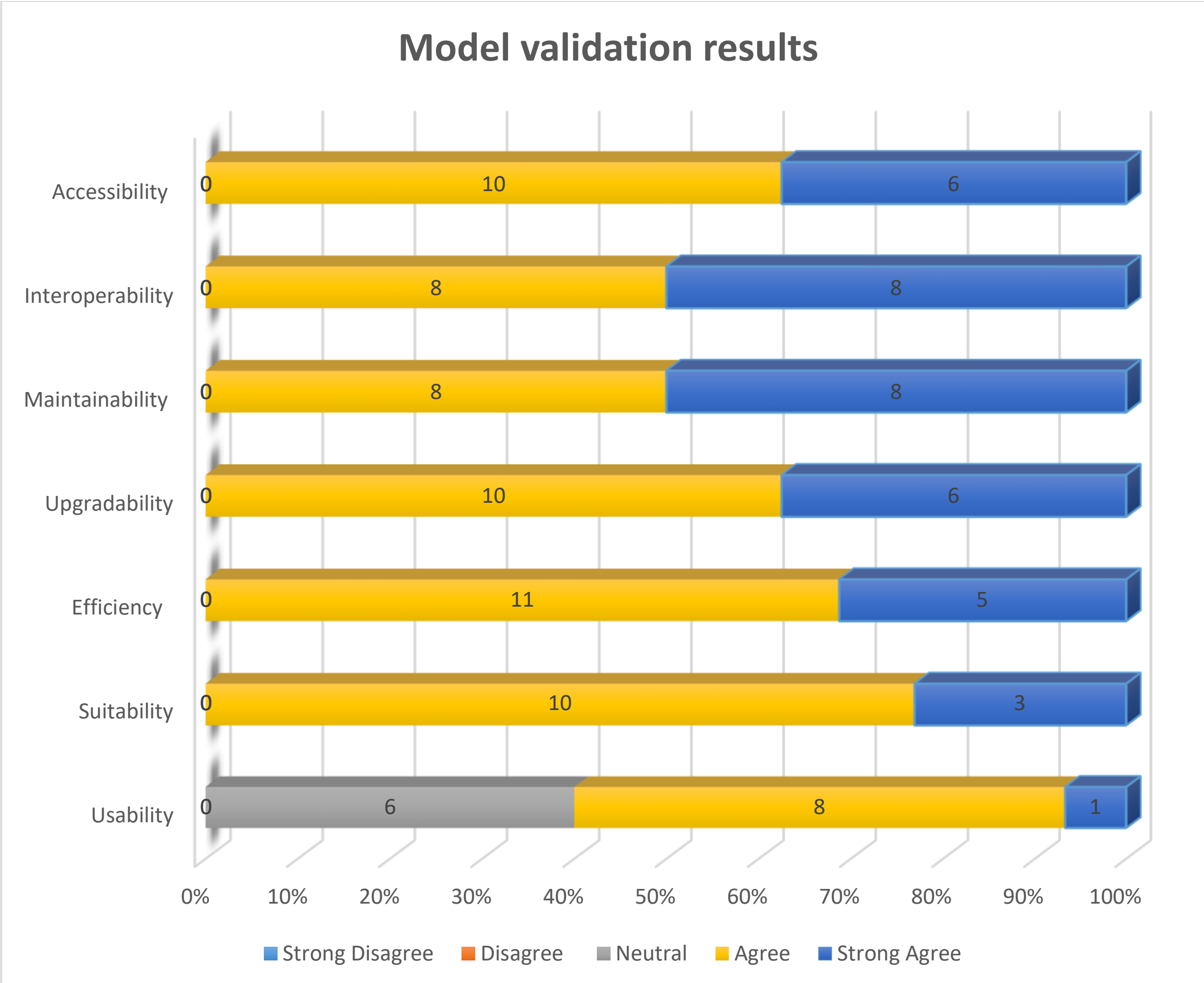

Figure 19: Operation Validation Results

4.2 Discussion

This study aimed to develop an integrated machine learning based quality measurement model for Tanzania's maternal, neonatal and child health services. The development of this model was motivated by a lack of an effective approach to measuring and reporting on the quality of MNCH services provided to pregnant women and children in Tanzania. This has also well stressed by other scholars. For instance, the studies by Kruk *et al.* (2016b) and Akachi and Kruk (2017) emphasized quality measurement and reporting. Therefore, the present study introduces to the body of knowledge a new technological and resource-efficient quality measurement model for MNCH quality measurement. It also addresses the challenges that impede the effectiveness of quality measurement process. In this technological era, the world requires intelligent systems that can be integrated and work together to enhance resource sharing and improve performance. The developed quality measurement model is a machine learning-based approach. It is designed to measure the quality of MNCH services provided, by identifying the trends and patterns from the data, a task which would not be apparent to human beings. With machine learning, there is no need to babysit the quality measurement process every step of the way because here the machine is given ability to learn and categorize the data by itself.

Additionally, a machine learning algorithms and models used to gain experience and keep improving in accuracy and efficiency as they are applied. This enables the developed model measure quality in a better was when used over and over again. Therefore, the developed quality measurement model is an intelligent system that requires only a few resources to accomplish quality measurement. The developed quality measurement model deploys data from DHIS 2 data warehouse to measure the quality of MNCH services. The DHIS 2 is currently used as a centralized database and national health information system in Tanzania (Karuri *et al.,* 2014). Routine health data collected from health facilities are stored in this data warehouse.

Five years of maternal and child health routine data collected daily from all health facilities that provide maternal and child health in Tanzania were congregated to form a dataset for this study. The used data were readily available in DHIS 2 data warehouse, thus removing the intense and laborious work of data collection tools preparation and data collection for quality measurement. Also, using these data prevents and removes the drawbacks associated with data from other sources like surveys and medical reports. It makes the developed quality measurement model an intelligent system that enhances resource sharing and improves performance.

In developing a new and better approach for maternal and child health quality measurement, the study has also addressed various factors facing the entire quality measurement process in Tanzania. The first factor was lack of standard quality measurement approach that is tailored to suit Tanzania quality measurement context. The literature showed that despite the existing quality measurement approaches being ineffective; a standard quality measurement approach that is specific to Tanzania quality measurement needs was also missing. Tanzania has been using facility-based quality measurement approaches for MNCH quality measurement. Service availability and readiness assessment (SARA) was used in 2012 (URT, 2013). Service Delivery Indicator (SDI) used in 2016 (Bold *et al.,* 2011), Service Provision Assessment (SPA) used in 2014-2015 (MoHSW *et al.,* 2015) and needs assessment for emergency obstetric and newborn care (EmONC) which was used in several regions in different time in Tanzania (Bintabara *et al.,* 2019; Lakhani *et al.,* 2017; Muhammad, 2015).

Despite the usefulness of these approaches none of these was considered standard quality measurement tool and adopted for quality measurement in Tanzania. The lack of a standard quality measurement approach or nationally approved quality measurement approach limits the quality measurement in the country and minimizes the quality measurement frequency. Kruk *et al*. (2016b) emphasized that to reduce maternal and neonatal deaths developing countries must systematically measure and report the quality of MNCH services. Tanzania and other developing countries with high maternal and child mortality need dedicated and sustainable quality measurement approaches. The developed quality measurement model is tailored to suit the Tanzanian quality measurement requirements. If approved, the model has the potential to be adopted as a standard quality measurement approach in Tanzania and also in other resource-constrained countries.

Second factor was quality indicators for quality measurement. Quality indicators were found to be essential in quality measurement processes. However, the study found that in Tanzania, neither the quality indicators selection procedure nor the quality indicators list was made available for quality measurement requirements (Saturno-Hernández *et al.*, 2019; Warren *et al.*, 2014). This study filled this gap by identifying the quality measurement indicators. Twenty-nine indicators were identified as suitable for quality measurement using a random forest classifier. Further selection using a random forest selector yielded eight indicators: Maternal mortality ratio, still-birth rate, delivery at the health facility, deliveries assisted by skilled attendants, proportional breech delivery, normal delivery rate, born before arrival rate and antenatal care visit coverage. These eight ones are considered to be the most important indicators for quality measurement. This study, therefore, considers a set of eight indicators as the best set of indicators and recommends them to be used for quality measurement in MNCH.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study developed an integrated machine learning based quality measurement model for maternal, neonatal and child health services in Tanzania. The study was motivated by high maternal and neonatal death occurrences in developing countries, especially in sub-Saharan Africa and Tanzania inclusive. The revised literature stressed the poor quality of MNCH services provided to pregnant women and children as an underline cause of high death occurrences. The literature further revealed that the death causes are much known, and the majority could be prevented if women and children had access to quality MNCH services. Therefore, the quality of MNCH is an underpinned factor in reducing maternal and neonatal deaths.

The first specific objective of the study, "analysis of the existing quality measurement approaches used in Tanzania" revealed that: (a) There is no existence of quality measurement approach explicitly developed to suit Tanzania's MNCH quality measurement requirements, (b) Quality measurement approaches currently used to measure the quality of MNCH services are inadequate, (c) Lack of a standard quality measurement approach is considered a gold standard for quality measurement in Tanzania. The available quality measurement approaches are said to be manual and paper-based; where by the whole quality measurement process, from data collection to quality measurement results dissemination, is done manually. This lead to laborious and resource intensive activity that resulting into poor MNCH quality measurement process and infrequent MNCH quality measurement hence unestablished MNCH quality status.

The second specific objective of the study "development of the proposed quality measurement model" was accomplished using an unsupervised machine learning algorithm (K-means). During data preparation for the machine learning experiment, a list of important indicators for quality measurement was derived. The quality indicators were used to develop quality measurement model (clustering model). The identified a list of important quality indicators for MNCH quality measurement and machine learning based quality measurement model are essential input in effective quality measurement process.

The third specific objective of the study "model validation" validated the model's effectiveness in quality measurement. The process included conceptual and operational validation to ensure the model's suitability in MNCH quality measurement. The validation process was carefully done with the help of reproductive and child health (RCH) coordinators and a few MNCH experts. The

MNCH experts, stakeholders and health workers accepted the developed model as a suitable and efficient approach for the quality measurement process in Tanzania.

5.2 Recommendations

5.2.1 Recommendations to the Maternal, Neonatal and Child Health Experts and Stakeholders

During quality measurement model development, the study found that: (a) Lack of standard quality measurement approach; despite the variety of quality measurement approaches available and used for quality measurement in Tanzania, and (b) Lack of universal accepted quality indicators list for quality measurement. In one way or another, the lack of a quality measurement approach and a list of quality measurement indicators hamper the quality measurement process and limit the effectiveness of quality measurement approaches. With these observations, the study recommends the developed quality measurement model and the list of quality measurement indicators for the MNCH quality measurement this study put forth. Poor selection of quality indicators impedes quality measurement exercise and may jeopardize the quality measurement results. Looking for an approach whenever there is a need to measure MNCH quality and customizing the identified approach to suit the specific quality measurement requirement adds overhead processes to the quality measurement exercise. The overhead processes associated with financial implications may lead to infrequent quality measurement. The study also recommends that the procedures for quality indicator selection should be defined and published for public use.

5.2.2 Recommendations to Policy Makers

The quality of MNCH care results from several factors, and the proposed quality measurement approach is not a holistic solution to poor MNCH quality. The study introduced the Machine Learning based quality measurement approach. However, the digitization level of society and users, especially MNCH experts and Reproductive Health Coordinators' computer literacy, are issues of concern. This study will not directly impact the digitization of society or the computer literacy of users. However, it may indirectly support society's digitization, improve users' computer skills, and add value to the quality standards of MNCH care. It is one stone among the needed ones to improve the quality of MNCH care.

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APPENDICES

Appendix 1: Survey Questionnaire

Survey questionnaire for integrated quality measurement model for maternal, neonatal and child health services in Tanzania

Dear Respondent!

I am Sarah Nyanjara, a candidate from Nelson Mandel African institution of Science and Technology – Arusha (NM-AIST). I am pursuing a doctor of philosophy degree (Ph.D). My Ph.D study titled "integrated quality measurement model for maternal, neonatal and child health services in Tanzania". The study specifically intends to put in place resource efficient quality measurement approach for effective quality measurement of maternal and child health services. This survey questioner intends to collect data/information that will facilitate model validation. Your participation is valuable for successfully completion of model validation and ensure suitability of the model for quality measurement in Tanzania.

1. How well can you describe the demonstrated approach for quality measurement?
    a) Poor quality measurement approach
    b) Satisfactory quality measurement approach
    c) Good quality measurement approach
    d) Excellent quality measurement approach

2. How well does the demonstrated approach meet quality measurement needs?
    a) Do not meet quality measurement needs
    b) Somehow meet quality measurement need
    c) The approach meets quality measurement needs

3. What is the strength of the demonstrated approach in quality measurement?

    ……………………………………………………………………………………….

4. What are the weaknesses of the demonstrated approach in quality measurement?

    ……………………………………………………………………………………….

5. What is/are important things/features that you think the approach is missing

    ……………………………………………………………………………………….

6. What would you like to change in the quality measurement model?

    ……………………………………………………………………………………….

7. How easy is it to use quality measurement model for quality measurement?
    a) It is not easy
    b) It is somehow easy
    c) It is easy

8. Were you able to understand the quality measurement results?
    a) Yes
    b) No

9. Compared to existing quality measurement approaches; how do quality measurement model perform
    a) Poor
    b) Satisfactory
    c) Good

10. Why would you choose quality measurement model over the traditional quality measurement approaches (select all which are appropriate)
    - It is easy and convenient to use
    - It is effective in quality measurement
    - It is resourceful in quality measurement

11. Do you agree with the following statement "the quality measurement model is effective in MNCH quality measurement"?
    a) I disagree
    b) Neutral
    c) I agree

12. On a scale of 0 to 5 how likely are you to recommend the quality measurement model for quality measurement in Tanzania. ………………….

    0 – Strongly not recommend
    1 - Not recommend
    2 – Not recommend unless further amendment to add ……………. or remove ………….
    3 – Recommend with addition of ……………. or removal of …………………….
    4 – Recommend
    5 – Strongly recommend

13. What will you say to someone who ask about quality measurement model?
    a) Poor approach not suitable for quality measurement in Tanzania
    b) Satisfactory approach may be suitable for quality measurement in Tanzania
    c) Excellent approach suitable for quality measurement in Tanzania

Appendix 2: Summary of Quality Measurement Approaches

Author (s)	Study/ Programme	ICT application	Domain in MNCH	Objective	Data source	Type and Component assessed	Country Implemented
(Kruk et al., 2016a)	Quality of basic maternal care functions in health facilities of five African countries: an analysis of national health system surveys	None	Maternal health	To analyze the quality of basic maternal care functions and its association with volume of deliveries and surgical capacity in health-care facilities in five sub-Saharan African countries	Health system surveys (Service Provision Assessments by the Demographic and Health Survey Programme) with data for volume of deliveries and quality of delivery care from Kenya, Namibia, Rwanda, Tanzania, and Uganda.	Structure and Component	Kenya, Namibia, Rwanda, Tanzania, and Uganda.
(Brazil, 2008)	Quality assessment of labor care provided in the Unified Health System in Rio de Janeiro, Southeastern Brazil, 1999–2001	None	Obstetric care	The objective of the study was to assess quality of labour care by gestational risk and type of health provider	Observational, cross-sectional study of labour care provided to 574 pregnant women. Stratified sampling in 20 Unified Health System maternity hospitals in Rio de Janeiro, Brazil, was carried out between 1999 and 2001	Process	Brazil
(Moresti n et al., 2010)	Evaluating quality of obstetric care in low-resource settings: Building on the literature to design tailor-made evaluation instruments - An illustration in Burkina Faso	None	Obstetrics care	Tools development to guide the choice of instruments and describe how we used them in Burkina Faso to facilitate the participative development of a locally adapted instrument.	Facility records	Structure, process and outcome	Burkina Faso
(Canavan et al., 2017)	Maternal and neonatal services in Ethiopia: measuring and improving quality	None	Maternal and Neonatal	Development and testing a method of measuring the quality of maternal and neonatal care that could be embedded in	The tool used direct observations and medical record reviews to score	Structure and process	Ethiopia

				a larger national performance management initiative.	quality in nine domains of intrapartum care.		
(Sprague et al., 2013)	Measuring Quality in Maternal-Newborn Care: Developing a Clinical Dashboard	None	Maternal and Newborn	Develop a maternal-newborn dashboard to increase awareness about selected KPIs and to inform and support hospitals and care providers about areas for quality improvement	Facility records	Process	Canada
(Chawla & Darlow, 2018)	Development of Quality Measures in Perinatal Care – Priority for Developing Countries	None	Neonatal and Perinatal	Development of Quality Measures in Perinatal Care	Direct observation, existing records, and interview of the involved stakeholders	Structure, Process and Outcome	Developing Countries
(Tripathi et al., 2015)	Development and Validation of an Index to Measure the Quality of Facility-Based Labour and Delivery Care Processes in Sub-Saharan Africa	None	Maternal and Neonatal	To identify key dimensions of the quality of the process of intrapartum and immediate postpartum care (QoPIIPC) in facility deliveries and developed a quality assessment measure representing these dimensions.	A comprehensive delivery observation checklist used in quality surveys in sub-Saharan African countries. Potential QoPIIPC indices were developed from combinations of highly-rated indicators. Face, content, and criterion validation of these indices was conducted using data from observations of 1,145 deliveries in Kenya, Madagascar, and Tanzania (including Zanzibar).	Process	Sub-Saharan Africa
(Penney & Fitzmaurice, 2002)	To compare data obtained from two sources, service providers and service users, regarding the maternity services in Scotland	None	Maternal health	To assess the quality of maternity care	comparison of data obtained from service providers and service users regarding the maternity services in Scotland (document review)	Process	Scotland
(Pazandeh et al., 2015)	An evaluation of the quality of care for women with low-risk pregnancy: The use of evidence-based practice during	None	Labor and childbirth	Evaluation of the quality of care for women with low-risk pregnancy	Evidence-based practice (observation) and Interview	Process	Iran

	labour and childbirth in four public hospitals in Tehran						
(Ambruoso & Achadi, 2009)	Assessing quality of care provided by Indonesian village midwives with a confidential enquiry	None	Maternal	To conduct a confidential enquiry to assess the quality of care provided by Indonesian village midwives and to identify opportunities for improvement.	The reviews based on transcripts of interviews with health- care providers, family and community members involved in the cases	Process and Structure	Indonesia
(Guzha et al., 2018)	Assessment of quality of obstetric care in Zimbabwe using the standard primipara	None	Obstetrics Care	Assessing the quality of Obstetric Care	hospital discharge data	Process and Structure	Zimbabwe
(Wanzira et al., 2018)	Quality of care for children with acute malnutrition at health center level in Uganda: a cross sectional study in West Nile region during the refugee crisis	None	Child health	Assessing health services provided to children with malnutrition	National Nutrition Service Delivery Assessment Tool	Process	Uganda
(Lynam, 1994)	Client Flow Analysis (CFA) A Practical Management Technique for Outpatient Clinic Settings	None	Family Planning	Look how patients move through the clinic, monitor waiting time, contact time and identify bottlenecks and areas of poor staff utilization	Facility data	Structure, Process	Not specified
(Pamela Lynam, 1993)	Client-Oriented, Provider-Efficient (COPE)	None	Family Planning	Development of checklist aided self-assessment, client	Client interview	Structure, Process	Not specified
(Sprockett, 2017)	Profiles of Health Facility Assessment Methods (ELMS)	None	Family Planning	Assessment of the availability of resources in facilities providing long-acting and permanent Method contraceptive options. It evaluates staffing, referral capability, physical facilities, medicines, basic equipment, provider knowledge and qualification and client	Facility data	Structure, Process	Tanzania, Bangladesh, Bolivia and Azerbajain

				satisfaction, among other components of quality			
(Hozumi et al., 2008)	Facility Audit of Service Quality (FASQ)	None	Primary Health Care	Assesses facility infrastructure, equipment and the quality of care provided.	Facility data	Structure	Not specified
(Sprockett, 2017)	Facility Based Assessment (FBA)	None	Child health	The FBA evaluates the extent to which children are appropriately diagnosed and treated at health facilities	Uses observation of provider performance, exit interviews with child caretakers, provider interviews, record review, and an inventory of essential equipment and supplies.	Structure, and Process	Nigeria, Burundi, Central African Republic, Republic of Congo, guinea, Malawi, Togo, Swaziland and Cote d'Ivoire
(Hozumi et al., 2008)	Health Facility Census (HFC)	None	Primary Health Care	This tool assesses the physical assets in the health sector with primary design for policy, planning and management of the health system	Facility data	Structure	Malawi, Zambia
(Groene, 2016)	Performance Assessment Tool for Quality Improvement in Hospitals (PATH)	None	Primary health care	This performance assessment tool Examines clinical effectiveness, efficiency, staff orientation, responsive governance, safety and patient centeredness.	Facility health data	Structure, and Process	High Income Countries also tested in South Africa
(Sprockett, 2017)	Performance Monitoring and Accountability (PMA 2020)	None	Reproductive Health	Monitor nationally representative family planning indicators that support the FP2020 goals. PMA2020 collects, analyzes and disseminates data on access, quality, equity, demand and utilization.	This tool uses standardized questionnaires, modified to the local context	Structure and Process	The work is implemented by local universities and research organizations in the nine countries where PMA2020 operates

(Sprockett, 2017)	Population Council Health Facility Assessment (HFA)	None	Primary Health Care	The Population Council HFA allows reproductive health programme managers to benchmark the performance of health facilities. The tool is primarily designed for planning purposes, especially for strategic health planning, monitoring, and evaluation, although it may also be used while piloting service quality improvements	Facility Data	Structure and Process	Not specified
(Sprockett, 2017)	Primary Care Assessment Tool (PCAT)	None	Adolescence health	The PCAT include client, facility, provider and health system surveys to assess quality of primary healthcare	Health system surveys	Structure and Process	China and Brazil
(World Health Organization, 2009)	Quality Assessment Guidebook for Adolescent Services	None	Adolescent health	This WHO tool assesses the quality of services for adolescents. Although it is unwieldy to use all recommended data collection instruments for each quality component, the tool recommends using at least two instruments to assess each quality component, adapting the instruments to the local context	Facility Data	Structure and Process	Not specified
(Investigation, n.d.)	Quick Investigation of Quality (QIQ)	None	Family planning	The QIQ, a subset of the SPA, uses a shortlist of indicators to assess family planning clinic quality every 1-2 years.	The tool uses a facility audit, provider observation and client exit interviews	Structure and Process	Uganda, Zimbabwe, Morocco, Ecuador and Turkey
(Sprockett, 2017)	Rapid Health Facility Assessment (R-HFA)	None	Maternal, Neonatal and Child health	The R-HFA measures a small set of indicators for maternal, newborn and child health services in primary care to identify bottlenecks in service delivery.	Facility health data	Structure and Process	Not specified

(Sprockett, 2017)	Rapid Service Quality Assessment (RSQA) Service Delivery Indicator (SDI The RSQA, produced by The Global Fund to Fight AIDS, Tuberculosis, and Malaria	None	Malaria, HIV and TB	Designed to assess service Quality under national disease programmes	Facility Health data and Survey	Structure	Not specified
(Sprockett, 2017)	Health Survey Instrument	None	Not specified	The Health Survey Instrument assesses education and health service delivery quality and performance from a Citizen's perspective.	Survey	Structure and Process	Kenya, Mozambique, Turkey, Uganda and Zimbabwe
(Hozumi et al., 2008)	Service Availability Mapping (SAM)	None	Child health and Reproductive Health	Although it was the first quantitative tool to measure access to reproductive and child health services, it has been replaced by the Service Availability and Readiness Structure Assessment	the WHO's SAM tool collects basic information on health infrastructure, human resources, and available services	Structure	Not specified
(World Health Organization, 2014)	Service Availability and Readiness Assessment (SARA)	None	Maternal, neonatal, Family planning, HIV, TB, Malaria and Child Health	Assess health facility service delivery. A standard set of core questions that address facility type, managing authority, national service guidelines, staffing categories and national medicines policies allow for comparisons across and within countries	Uses rapid data collection and analysis	Structure, process	Not specified
(Hozumi et al., 2008)	**The Service Provision Assessment (SPA)**	None	Maternal, Neonatal and Child Health, Family	They collect information on the overall availability of different facility-based health services in a country and their readiness to provide those services.	The tool uses a facility inventory provider interview, provider observation, and client exit interview	Structure	Tanzania, Ethiopia, Ghana, Kenya, Rwanda, Senegal, Zambia, Malawi, Uganda,

			Planning, Malaria, TB and HIV/AIDS				Haiti, Guatemala, Egypt, Guyana, Nepal, Bangladesh
(Hanson et al., 2014)	Expanded Quality Management Using Information Power (EQUIP)	None	Maternal and newborn health	Assess quality management at the district, facility, and community levels, supported by information from high-quality, continuous surveys, and report effects of the quality management intervention on the utilization and quality of services in Tanzania and Uganda.	Independent continuous household and health facility surveys	Structure and Process	Tanzania and Uganda.
(Mcginn et al., 2011)	Supply-Enabling Environment-Demand (SEED) With an emphasis on long-acting family planning methods, this tool was designed by Engender Health	None	Family planning	to assess an organization's capacity to provide family planning services	Literature, key informant interviews, analysis and write-up of a final report and discussion with key stakeholders and partners	Structure,	Not specified

Appendix 3: Feature Selection Sample Codes

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

# Set the style globally
# Alternatives include bmh, fivethirtyeight, ggplot,
# dark_background, seaborn-deep, etc
plt.style.use('seaborn-white')
plt.rcParams['font.family'] = 'DejaVu Sans'
plt.rcParams['font.serif'] = 'Ubuntu'
plt.rcParams['font.monospace'] = 'Ubuntu Mono'
plt.rcParams['font.size'] = 20
plt.rcParams['axes.labelsize'] = 16
plt.rcParams['axes.labelweight'] = 'bold'
plt.rcParams['xtick.labelsize'] = 16
plt.rcParams['ytick.labelsize'] = 16
plt.rcParams['legend.fontsize'] = 16
plt.rcParams['figure.titlesize'] = 12
plt.rcParams['figure.figsize'] = 8, 6
```

In [2]:
```
#load cleaned data
data = pd.read_csv('MaternalDataset.csv')
data.head()
```

Out[2]:

	ANC visit Dropout Rate	ANC Visit Before 12 Weeks Rate	ANC Visit Coverage	ANC 4th visits Coverage	ANC Anaemia Prevalance	ANC HIV testing rate	ANC HIV+ given ART rate	ANC HIV+ given ARV	ANC IPT 1 coverage	A co
0	59.3	0.0	0.0	0.0	1.3	92.8	76.1	56.5	48.9	30.
1	52.6	0.0	0.0	0.0	1.1	97.9	65.1	104.8	38.0	30.
2	64.1	0.0	0.0	0.0	2.1	88.2	27.5	48.4	31.9	23.
3	65.4	0.0	0.0	0.0	1.2	86.3	22.7	22.7	69.2	53.
4	72.3	0.0	0.0	0.0	2.7	89.7	108.7	60.9	43.7	29.

5 rows × 50 columns

1.2. Model - based feature Selection : Using Feature Importance

Using RandomForest Classifier

In [3]:
```
# Load the packages for modeling
from sklearn.ensemble import RandomForestClassifier
```

```
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:2
9: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module and
should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [4]:
```
# Define a classifier
rforest = RandomForestClassifier(max_depth=15,n_estimators=70, min_samples_lea
f=50,
                                  min_samples_split=100, random_state=10)
```

In [5]:
```
# Prepare Feature and Target
data.columns
```

Out[5]:
```
Index(['ANC visit Dropout Rate', 'ANC Visit Before 12 Weeks Rate',
       'ANC Visit Coverage', 'ANC 4th visits Coverage',
       'ANC Anaemia Prevalance', 'ANC HIV testing rate',
       'ANC HIV+ given ART rate', 'ANC HIV+ given ARV', 'ANC IPT 1 coverage',
       'ANC IPT 2 coverage', 'ANC IPT 4 coverage', 'ANC Total Visits',
       'ANC Malaria testing rate', 'ANC PMTCT protection  rate ',
       'ANC-Combined Treatment', 'ANC women receiving TT2+',
       'ANC tested for Anaemia', 'ANC tested for Syphilis',
       'ANC de-worming rate', 'ANC women receiving 2 doses of SP',
       ' Institutional delivery coverage', 'ANC HIV counseling and testing',
       'ANC Iron Folic supplementation', 'ANC treated for Syphilis',
       ' EOC Rate', 'Deliveries by Caesarean Section',
       'Institutional Deliveries', ' ARV at Birth Rate', ' BBA Delivery Rat
e',
       ' Delivery Abnormal', 'Delivery Complications rate',
       'Home Delivery rate', ' LBW (Twins)', 'LBW (single)',
       'Normal Delivery rate', 'Percent of Born Before Arrival',
       'Proportion of Breech Delivery', 'Kangaroo mother care',
       'Deliveries  developed PPH',
       'Deliveries assisted by skilled attendants', 'Deliveries by vacuum',
       'Deliveries referred out', 'Newborn birth weight <2.5kg ',
       'Newborn initiated early breastfeeding ', 'Newborn resuscitated',
       'Delivery at HF', 'Stillbirth rate ', 'TBA rate',
       'Maternal Mortality Ratio', 'Quality'],
      dtype='object')
```

In [6]:
```
#Deleting Unwanted Columns
```


In [7]:
```
data.drop ([' LBW (Twins)', 'LBW (single)', 'ANC Visit Before 12 Weeks Rate',
'ANC Total Visits', 'Kangaroo mother care'], axis=1)
```

Out[7]:

	ANC visit Dropout Rate	ANC Visit Coverage	ANC 4th visits Coverage	ANC Anaemia Prevalance	ANC HIV testing rate	ANC HIV+ given ART rate	ANC HIV+ given ARV	ANC IPT 1 coverage	ANC IPT coverag
0	59.3	0.0	0.0	1.30	92.8	76.1	56.5	48.90	30.2
1	52.6	0.0	0.0	1.10	97.9	65.1	104.8	38.00	30.3
2	64.1	0.0	0.0	2.10	88.2	27.5	48.4	31.90	23.0
3	65.4	0.0	0.0	1.20	86.3	22.7	22.7	69.20	53.1
4	72.3	0.0	0.0	2.70	89.7	108.7	60.9	43.70	29.1
5	60.8	0.0	0.0	3.20	93.0	59.5	21.6	19.20	11.6
6	70.7	0.0	0.0	1.40	85.5	13.8	44.8	41.90	27.1
7	60.9	54.0	26.3	0.79	96.1	100.0	25.7	48.00	49.9
8	52.8	35.6	21.0	0.76	98.8	126.3	22.3	64.30	52.6
9	43.5	94.6	66.9	1.40	95.1	123.2	37.3	51.00	50.0
10	53.1	45.5	26.7	1.20	94.8	94.2	59.6	55.80	44.7
11	63.1	45.8	21.1	0.34	95.6	118.6	52.9	66.30	57.4
12	70.0	52.1	19.5	2.20	93.4	99.0	19.6	46.00	42.1
13	60.5	59.5	29.4	1.20	98.9	100.0	28.9	75.10	66.5
14	51.7	48.7	29.4	1.30	98.9	0.0	0.0	0.00	96.4
15	41.5	35.4	25.9	0.56	98.7	0.0	0.0	1.40	82.0
16	31.1	89.6	77.1	1.70	99.1	0.0	0.0	0.00	84.1
17	29.2	45.2	39.9	0.60	99.7	0.0	0.0	0.09	78.7
18	47.2	44.6	29.4	0.45	97.0	0.0	0.0	0.06	89.2
19	52.4	47.8	28.4	0.91	99.3	2.8	0.0	0.42	69.2
20	56.5	60.6	33.0	1.50	99.3	0.0	0.0	0.00	75.8
21	35.7	52.1	41.9	1.50	98.9	0.0	0.0	0.00	98.1
22	38.4	34.7	26.7	0.71	98.6	0.0	0.0	0.00	82.6
23	41.2	89.2	65.6	1.20	99.2	0.0	0.0	0.00	102.4
24	18.8	43.9	44.6	0.77	98.7	0.0	0.0	0.00	89.0
25	28.0	44.1	39.7	0.43	99.1	0.0	0.0	0.00	102.0
26	40.8	48.6	36.0	1.90	99.3	0.0	0.0	0.00	74.1
27	50.6	57.7	35.6	1.00	95.0	0.0	0.0	0.00	84.4
28	43.2	52.3	37.1	1.10	99.1	0.0	0.0	0.00	87.2

	ANC visit Dropout Rate	ANC Visit Coverage	ANC 4th visits Coverage	ANC Anaemia Prevalance	ANC HIV testing rate	ANC HIV+ given ART rate	ANC HIV+ given ARV	ANC IPT 1 coverage	ANC IP 2 coverag
29	40.6	36.4	27.0	0.84	98.6	0.0	0.0	0.00	65.7
...	...	...	...	...	...	...	...	...	...
495	60.8	0.0	0.0	3.20	93.0	59.5	21.6	19.20	11.6
496	70.7	0.0	0.0	1.40	85.5	13.8	44.8	41.90	27.1
497	60.9	54.0	26.3	0.79	96.1	100.0	25.7	48.00	49.9
498	52.8	35.6	21.0	0.76	98.8	126.3	22.3	64.30	52.6
499	43.5	94.6	66.9	1.40	95.1	123.2	37.3	51.00	50.0
500	53.1	45.5	26.7	1.20	94.8	94.2	59.6	55.80	44.7
501	63.1	45.8	21.1	0.34	95.6	118.6	52.9	66.30	57.4
502	70.0	52.1	19.5	2.20	93.4	99.0	19.6	46.00	42.1
503	60.5	59.5	29.4	1.20	98.9	100.0	28.9	75.10	66.5
504	51.7	48.7	29.4	1.30	98.9	0.0	0.0	0.00	96.4
505	41.5	35.4	25.9	0.56	98.7	0.0	0.0	1.40	82.0
506	31.1	89.6	77.1	1.70	99.1	0.0	0.0	0.00	84.1
507	29.2	45.2	39.9	0.60	99.7	0.0	0.0	0.09	78.7
508	47.2	44.6	29.4	0.45	97.0	0.0	0.0	0.06	89.2
509	52.4	47.8	28.4	0.91	99.3	2.8	0.0	0.42	69.2
510	56.5	60.6	33.0	1.50	99.3	0.0	0.0	0.00	75.8
511	35.7	52.1	41.9	1.50	98.9	0.0	0.0	0.00	98.1
512	38.4	34.7	26.7	0.71	98.6	0.0	0.0	0.00	82.6
513	41.2	89.2	65.6	1.20	99.2	0.0	0.0	0.00	102.4
514	18.8	43.9	44.6	0.77	98.7	0.0	0.0	0.00	89.0
515	28.0	44.1	39.7	0.43	99.1	0.0	0.0	0.00	102.0
516	40.8	48.6	36.0	1.90	99.3	0.0	0.0	0.00	74.1
517	50.6	57.7	35.6	1.00	95.0	0.0	0.0	0.00	84.4
518	43.2	52.3	37.1	1.10	99.1	0.0	0.0	0.00	87.2
519	40.6	36.4	27.0	0.84	98.6	0.0	0.0	0.00	65.7
520	41.0	90.4	66.7	1.40	97.7	0.0	0.0	0.00	92.4
521	12.1	43.1	47.4	0.93	98.7	0.0	0.0	0.00	83.6
522	30.0	45.4	39.7	0.31	98.4	0.0	0.0	0.00	54.4

	ANC visit Dropout Rate	ANC Visit Coverage	ANC 4th visits Coverage	ANC Anaemia Prevalance	ANC HIV testing rate	ANC HIV+ given ART rate	ANC HIV+ given ARV	ANC IPT 1 coverage	ANC IPT 2 coverage
523	41.2	50.4	37.0	1.40	99.2	0.0	0.0	0.00	75.5
524	55.0	58.1	32.6	1.50	99.2	0.0	0.0	0.00	61.9

525 rows × 45 columns

In [8]:
```
data.columns
```

Out[8]:
```
Index(['ANC visit Dropout Rate', 'ANC Visit Before 12 Weeks Rate',
       'ANC Visit Coverage', 'ANC 4th visits Coverage',
       'ANC Anaemia Prevalance', 'ANC HIV testing rate',
       'ANC HIV+ given ART rate', 'ANC HIV+ given ARV', 'ANC IPT 1 coverage',
       'ANC IPT 2 coverage', 'ANC IPT 4 coverage', 'ANC Total Visits',
       'ANC Malaria testing rate', 'ANC PMTCT protection  rate ',
       'ANC-Combined Treatment', 'ANC women receiving TT2+',
       'ANC tested for Anaemia', 'ANC tested for Syphilis',
       'ANC de-worming rate', 'ANC women receiving 2 doses of SP',
       ' Institutional delivery coverage', 'ANC HIV counseling and testing',
       'ANC Iron Folic supplementation', 'ANC treated for Syphilis',
       ' EOC Rate', 'Deliveries by Caesarean Section',
       'Institutional Deliveries', ' ARV at Birth Rate', ' BBA Delivery Rat
e',
       ' Delivery Abnormal', 'Delivery Complications rate',
       'Home Delivery rate', ' LBW (Twins)', 'LBW (single)',
       'Normal Delivery rate', 'Percent of Born Before Arrival',
       'Proportion of Breech Delivery', 'Kangaroo mother care',
       'Deliveries  developed PPH',
       'Deliveries assisted by skilled attendants', 'Deliveries by vacuum',
       'Deliveries referred out', 'Newborn birth weight <2.5kg ',
       'Newborn initiated early breastfeeding ', 'Newborn resuscitated',
       'Delivery at HF', 'Stillbirth rate ', 'TBA rate',
       'Maternal Mortality Ratio', 'Quality'],
      dtype='object')
```

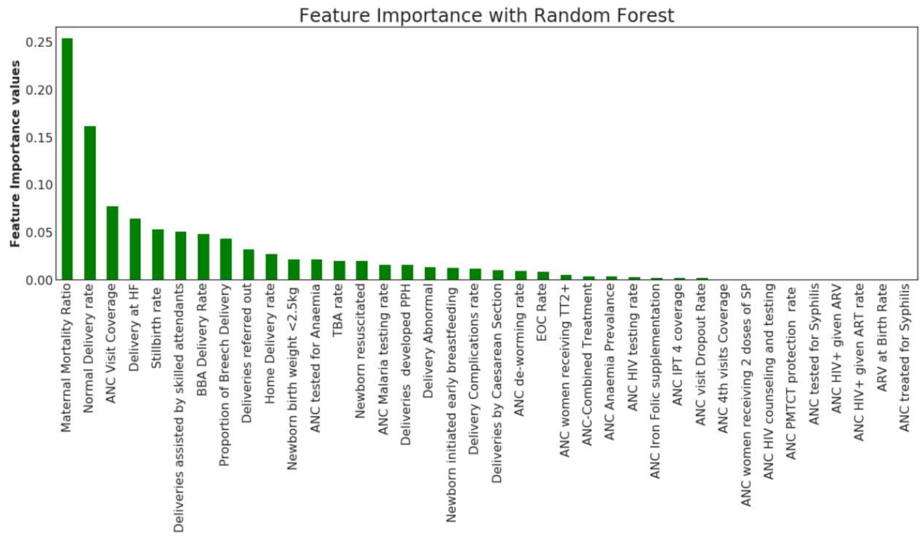
In [9]:
```
feature = ['ANC visit Dropout Rate',
       'ANC Visit Coverage', 'ANC 4th visits Coverage',
       'ANC Anaemia Prevalance', 'ANC HIV testing rate',
       'ANC HIV+ given ART rate', 'ANC HIV+ given ARV',
       'ANC IPT 4 coverage',
       'ANC Malaria testing rate', 'ANC PMTCT protection  rate ',
       'ANC-Combined Treatment', 'ANC women receiving TT2+',
       'ANC tested for Anaemia', 'ANC tested for Syphilis',
       'ANC de-worming rate', 'ANC women receiving 2 doses of SP',
       'ANC HIV counseling and testing',
       'ANC Iron Folic supplementation', 'ANC treated for Syphilis',
       ' EOC Rate', 'Deliveries by Caesarean Section',
       ' ARV at Birth Rate', ' BBA Delivery Rate',
       ' Delivery Abnormal', 'Delivery Complications rate',
       'Home Delivery rate',
       'Normal Delivery rate',
       'Proportion of Breech Delivery',
       'Deliveries  developed PPH',
       'Deliveries assisted by skilled attendants',
       'Deliveries referred out', 'Newborn birth weight <2.5kg ',
       'Newborn initiated early breastfeeding ', 'Newborn resuscitated',
       'Delivery at HF', 'Stillbirth rate ', 'TBA rate',
       'Maternal Mortality Ratio']
```

In [10]:
```
X = data[feature]
y = data.Quality
```

In [11]:
```
# Fit the model
rforest.fit(X,y)
```

Out[11]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=15, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=50, min_samples_split=100,
            min_weight_fraction_leaf=0.0, n_estimators=70, n_jobs=1,
            oob_score=False, random_state=10, verbose=0, warm_start=False)
```

In [12]:
```
# Plot the important features
imp_feat_rf = pd.Series(rforest.feature_importances_, index=X.columns).sort_va
lues(ascending=False)
imp_feat_rf.plot(kind='bar', title='Feature Importance with Random Forest', fi
gsize=(20,12),color='g')
plt.ylabel('Feature Importance values')
plt.subplots_adjust(bottom=0.50)
```



1.3 Model - based feature Selection : Using SelectFromModel

In [13]:
```
from sklearn.feature_selection import SelectFromModel

select = SelectFromModel(RandomForestClassifier(n_estimators=100, random_state
=42) , threshold="mean")
```

In [14]:
```
select.fit(X,y)
```

Out[14]:
```
SelectFromModel(estimator=RandomForestClassifier(bootstrap=True, class_weight
=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
            oob_score=False, random_state=42, verbose=0, warm_start=False),
        norm_order=1, prefit=False, threshold='mean')
```

In [15]:
```
X_features = select.transform(X)
print('Original features', X.shape)
print('Selected features', X_features.shape)
```

```
Original features (525, 38)
Selected features (525, 8)
```

Print the selected features

In [16]:
```
for feature_list_index in select.get_support(indices=True):
    print(feature[feature_list_index])
```

```
ANC Visit Coverage
 BBA Delivery Rate
Normal Delivery rate
Proportion of Breech Delivery
Deliveries assisted by skilled attendants
Delivery at HF
Stillbirth rate
Maternal Mortality Ratio
```

In [ ]:

Appendix 4: Ethical Clearance Certificate

Kibong'oto Infectious Diseases Hospital- Nelson Mandela African Institution of Science and Technology- Centre for Educational Development in Health, Arusha (KIDH-NM-AIST-CEDHA)

RESEARCH ETHICAL CLEARANCE CERTIFICATE

Research Proposal No: KNCHREC0006 **9TH October 2018**

Study Title: **Quality Measurement Framework for Maternal, Neonatal and Child Health Services in Tanzania**

Study Area: **THE NELSON MANDELA AFRICAN INSTITUTION OF SCIENCE AND TECHNOLOGY**

PI Name: Sarah Nyanjara

Co-Invigilator:

Institutions: School of Computational Science and Communication Engineering of the Nelson Mandela African Institution of Science and Technology

The Proposal has been approved by KNCHREC on 5th October 2018

1. **Subject to this approval you will be required to submit your progress report to the KNCHREC, National Institute of Research and Ministry of Health Community Development Gender Elderly and Children**
2. **Publication of your findings is subject to presentation to the KNCREC and NIMR Approval.**
3. **Copies of final publication should be made available to KNCHREC, National Institute of Research and Ministry of Health Community Development Gender Elderly and Children**

Duration of Study Renewal: Subject to Renewal within ONE YEAR

Span From: 5TH October 2018 to 4TH October 2019

....

Mr. Simon Njeya
Secretary
KNCHREC

Prof. Raymond Mosha
Chairperson
KNCHREC

RESEARCH OUTPUTS

Nyanjara, S., Machuve, D., & Nykanen, P. (2022) Maternal and Child Health Care Quality Assessment: An Improved Approach using *K*-Means Clustering. *Journal of Data Analysis and Information Processing*, 10, 170-183.

Nyanjara, S., Machuve, D., & Nykanen, P. (2022). Development of Machine Learning-Based Model for Quality Measurement in Maternal, Neonatal and Child Health Services: A Country Level Model for Tanzania. International Journal of Advances in Scientific Research and Engineering, (8)8, 11-22.

Nyanjara, S., Machuve, D., & Nykanen, P. (**In press**). Indicators Selection for Quality Measurement in Maternal Neonatal and Child Health Services: Application of Random Forest Classifier. *Journal of Software Engineering and Applications.*