LEVELS, ECONOMIC SAVINGS AND DETERMINANTS OF TECHNICAL EFFICIENCY IN PUBLIC HEALTH CENTRE III FACILITIES IN SOUTH WESTERN UGANDA

BY

MUGISHA INNOCENT

REG NO: 19/U/GAEE/20728/PE

A RESEARCH DISSERTATION SUBMITTED TO DIRECTORATE OF RESEARCH AND GRADUATE TRAINING IN PARTIAL FULLFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ARTS IN ECONOMICS OF KYAMBOGO UNIVERSITY

AUGUST 2023

DECLARATION

I Innocent Mugisha hereby declare that this work is original and a reflection of my efforts. It has never been submitted for any academic award in any university or institution for any award.

Signature…………………..

Date……………………......

APPROVAL

This is to certify that this research work by Innocent Mugisha entitled “Determinants of Technical Efficiency among Public Health Centre III Facilities in Southwestern Uganda” has been under our supervision. It has now been approved by us to be submitted to the graduate school.

Signature……………………

Date…………………………

Dr.Kenneth Tindimwebwa

Signature…………………….

Date…………………………

Dr.Lillian Namubiru

DEDICATION

This work is dedicated to my family. Thank you so much for the endurance and patience with me.

ACKNOWLEDGEMENTS

Great appreciation goes to the Almighty God, whose love, grace and mercy have helped me to successfully complete my studies and research work. The provisions for my studies were possible because of You, my God.

Great appreciation to Kyambogo University for the financial support through competitive research grant schemes for graduate student at research stage where I happen to be a beneficiary.

To my academic supervisors Dr. Kenneth Tindimwebwa and Dr. Lillian Namubiru, you made the whole process of research a reality. May the Almighty God reward you abundantly.

To all members of the Department of Economics, your support has been visible in this journey. Keep up the well-wishing heart.

Finally, to my course mates, we have walked this journey together, let us keep and expand the social circles. Blessings to you all.

TABLE OF CONTENTS

DECLARATION .... **i**

APPROVAL .... **ii**

DEDICATION .... **iii**

ACKNOWLEDGEMENTS .... **iv**

TABLE OF CONTENTS .... **v**

LIST OF TABLES .... **x**

ACRONYMS .... **xi**

ABSTRACT .... **xii**

CHAPTER ONE:BACKGROUND OF THE STUDY 1

1.0 Introduction 1

1.1 Background of the study 1

1.2 Statement of the Problem 7

1.3 Objectives of the Study 8

1.3.1 General Objective 8

1.3.2 Specific Objectives 8

1.4 Research Hypothesis 8

1.5 Scope of the Study 9

1.5.1 Geographical scope 9

1.5.2 Content scope 9

1.5.3 Time scope... 9

1.6 Significance of the Study 9

1.7 Organization of the Report.. 10

CHAPTER TWO: LITERATURE REVIEW.. 11

2.0 Introduction 11

2.1 The Concept of technical efficiency... 11

2.2 Hospital production process 12

2.3 Contextual literature review 13

2.4 Theoretical framework of technical efficiency 13

2.4.1 Property rights theory of technical efficiency 14

2.4.2 Agency theory of technical efficiency.. 14

2.5 Empirical literature... 15

2.5.1 Determinants of hospital technical efficiency 15

2.5.2 Economic savings from elimination of inefficiencies from healthcare facilities 16

2.5.3 Socioeconomic determinants of technical efficiency 17

2.6 Summary of the Literature overview 20

2.7 Conceptual framework of the study 21

CHAPTER THREE: METHODOLOGY 23

3.0 Introduction 23

3.1 Research Design 23

3.2 Data type and sources 23

3.3 Sampling techniques. 24

3.4 Sample criteria. 26

3.4.1 Stratification. 26

3.4.2 Probabilistic sampling technique. 26

This formed the second stage of sampling. 26

3.4.3 Simple random sampling technique. 26

3.5 Model description and specification 26

3.5.1 Data Envelopment Analysis (DEA) 27

3.5.2 DEA specification 28

3.6 DEA model variables selection 29

3.6.1 Input variables 29

3.6.2 Output variables 30

3.7 Socioeconomic factors for technical efficiency and tobit regression 31

3.7.1 Regression variables 31

3.7.2 Tobit Regression model 32

3.8 Ethical considerations 34

3.9 Data management and analysis 34

3.9.1 Management of data 34

3.9.2 Data Analysis... 34

CHAPTER FOUR:DATA PRESENTATION, ANALYSIS AND INTERPRETATION OF THE FINDINGS... 35

4.0 Introduction 35

4.1 Descriptive statistics for input and output variables 35

4.2 Estimation of Technical Efficiency (TE) scores for the HCIII facilities 37

4.3 Estimating the level of Economic saving from healthcare input reductions and output augmentations by inefficient facilities 43

4.4 Socioeconomic determinants of Technical Efficiency among HCIII facilities.................. 49

4.4.1 Multicollinearity test.. 51

4.4.2 Pairwise Correlation Analysis 52

4.4.3 Variance Inflation Factor (VIF)... 53

4.4.4 Tobit Regression model... 54

4.4.5 Discussion of Tobit regression results.. 57

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS OF THE STUDY 63

5.0 Introduction 63

5.1 Summary of the results 63

5.2 Study conclusions 64

5.3 Policy recommendations 65

5.4 Areas for further research 66

5.5 Study limitations 67

References 68

APPENDIX: DMU NAMES 80

LIST OF TABLES

Table 3.1: Showing variable description for the DEA model………………………………….. 25

Table 3.2: Sample size determination for the facilities………………………………..……. 30

Table 3.3: Socioeconomic characteristics of population……………………………………...31

Table 4.1: Descriptive statistics for input and output variables…………………………………36

Table 4.2: Technical Efficiency results and the benchmarks for the respective health facilities……………………………………………………………………………………. 38

Table 4.3: Slack values for health inputs and output variables………………………………… 44

Table 4.4: Descriptive statistics of the Socioeconomic factors………………………………… 50

Table 4.5: Showing the correlation coefficients between Explanatory variables for TE under Tobit model……………………………………………………………………………….. 52

Table 4.6: Showing VIF coefficients for the Tobit regression variables………………………...52

Table 4.7: Showing Tobit regression results for socioeconomic determinants of technical efficiency……………………………………………………………………………………54

ACRONYMS

ALoS:	Average Length of Stay
BOR:	Bed Occupancy Rate
CRS:	Constant Returns to Scale
DEA:	Data Envelopment Analysis
DHIS:	District Health Information Systems
DLG:	District Local Government
DMU:	Decision Making Unit
DPUs:	District Planning Units
EMHS:	Essential Medicines and Health Supplies
GDP:	Gross Domestic Product
HICs:	High Income Countries
LICs:	Low Income Countries
MoH:	Ministry of Health
NCDs:	Non Communicable Diseases
OPD:	Out Patient Department
TE:	Technical Efficiency
UBOS:	Uganda Bureau of Statistics
UNHS:	Uganda National Household Survey
VRS:	Variable Returns to Scale
WHO:	World Health Organization

ABSTRACT

Basic to human welfare is good health and it is fundamental for socioeconomic development of any economy. Faced with resource constraints especially in the health sector, technical efficiency among the healthcare agents is a global concern to ensure proper utilization of the scarce resources to deliver good healthcare services to people. About 20 to 40 percent of the 7.5trillion US dollars spent on health sector globally is wasted to inefficiency (Xu et al., 2018)**.**

The general objective was to investigate the determinants of Technical Efficiency in public Health center (HCIII) facilities in South Western Uganda. The study was guided by three specific objectives namely (i) to estimate the TE scores among HCIII facilities, (ii) to establish the level of economic savings that can be achieved when technically inefficient facilities achieved technical efficiency and finally (iii) to examine the socioeconomic determinants of technical efficiency in HCIII facilities in South Western Uganda.

The study uses a cross sectional descriptive research design with a sample of 30 public HCIII facilities in South Western Uganda. A Constant Returns to Scale (CRS) output-oriented Data Envelopment Analysis (DEA) technique was adopted to estimate TE and slack values for economic savings while a Tobit regression second stage model was applied for the socioeconomic determinants of TE among various public HCIII facilities. Secondary data was obtained from Uganda Bureau of Statistics (UBOS), District Health Information System (DHIS) and District Planning Units for health inputs and outputs as well as socioeconomic characteristics of the population in South Western Uganda for the financial year 2020/21.

The findings of the study reveal that 47 percent of the public HCIII facilities were technically efficient and the average TE score was 72 percent implying that the facilities need to improve resource utilization by 28 percent to become technically efficient.

The study concludes that unemployment rate, infectious diseases patients, catchment population, patient population below 5 and above 65 years, urban location and competition were the significant determinants of TE for HCIII facilities in South Western Uganda. The study finally recommends reallocation of resources within facilities, increasing resources for facilities and improving social services facilities to improve on the technical efficiency levels for HCIII facilities in South Western Uganda.

CHAPTER ONE

BACKGROUND OF THE STUDY

1.0 Introduction

This chapter presents the background of the study, the statement of the problem, and the objectives of the study. The research questions, the scope of the study, the significance of the study and the organization of the research report are also presented in this chapter.

1.1 Background of the study

Basic to human welfare is good health which in turn is fundamental to growth and development of any country (Emanuel et al., 2021). Accessing public healthcare services results often to the eradication of deadly diseases among the population and consequently improves their health status (Dominic et al., 2020).

Technical efficiency analysis is of great concern for stake holders and those in control of making policies worldwide in order to realize the universal health coverage goal amongst growing population. Major healthcare service providers such as hospitals and primary healthcare facilities are key in understanding technical efficiency in the health systems because they involve conversion of healthcare inputs and come up with healthcare outputs to meet the diverse healthcare demands across the globe (Mbau et al., 2023). Furthermore, assessing technical efficiency of health systems is essential for cost minimization and managing (Mohamadi et al., 2022).

Technical efficiency of healthcare systems largely determines the quality of services provided to the citizens of any country, making it important to evaluate of the functioning of the various healthcare system components (Top et al., 2020). Therefore, improving efficiency of the healthcare centers such as hospitals is important at all levels of operations of a healthcare system. Further, measuring hospital efficiency so as to respond to disparities that exist in the technical efficiency of similar level hospitals (Mahate et al., 2016). Considering the high and low levels of efficiency in healthcare facilities gives insights into what makes production processes work in their settings. Thus this helps in directing the supportive efforts to healthcare centers that need them most (Ayiko et al., 2020). These efficiency levels can be captured in the form of technical efficiency (TE) and scale efficiency (Mujasi et al., 2016).

Specifically, technical efficiency of any healthcare center also the decision making unit (DMU) is achieved through obtaining the highest possible output given health inputs and technology (Atake, 2019). Technical efficiency is categorized into pure technical and scale efficiency. On one side, pure technical efficiency technical denotes efficiency that cannot be attributed to deviations from optimal scale, on the other side scale efficiency measures the extent to which a health DMU deviates from optimal scale (Ayiko et al., 2020). In addition, technical efficiency manifests itself in the form of input-oriented or output-oriented approaches. The input-oriented approach focuses on using the minimum level of inputs to produce a stipulated output amount at a fixed technology, whereas output-oriented approach attempts to maximize output amount given inputs and fixed technology. In other words, the input-orientation seeks to minimize inputs while output-orientation seeks to maximize output given technology set (Davis, 2018).

Globally, about 7.5 trillion US dollars is spent on healthcare, representing close to 10 percent of global GDP, with an average per capita health expenditure of 1,000 US dollars (Xu et al., 2018). Notably, approximately 20 to 40 percent of the world’s expenditure on healthcare is wasted as a result of various inefficiencies which emphasizes the presence of a significant challenge to the global health systems (Xu et al., 2018). Lower Income Countries (LICs) are still lagging behind the high income countries (HICs) with estimated average per capita healthcare spending of over 2,000 US dollars for rich countries about 20 times higher than that of poor countries (100 US dollars) (Kohler & Bowra, 2020). This largely but not solely explains the better health outcomes in terms of improved life expectancy due to improved healthcare facilities and services in HICs than in LICs. Furthermore, higher public healthcare expenditure is generally associated with better health outcomes (Asbu et al., 2020).

Additionally, evidence is presented on deviating health indicators among the economic global circles specifically, the under-five, infant and neonatal mortality rates reported at 68.1, 48.1 and 26.4 for LICs compared to 5, 4.3 and 2.8 for HICs by 2018 respectively (Kohler & Bowra, 2020). This is justified by limited per capita income, income distribution injustice, paying less or no consideration to social state, national arrangement of health systems, and differences in goals, can be effective in separating efficiency among national health systems and have a great bearing on health outcomes and are less favorable in developing economies (Top et al., 2020).

In Sub-Saharan Africa (SSA), inefficiencies existing in the healthcare systems are mainly associated with scale inefficiencies. The fact that most of SSA countries are underdeveloped and economically depressed, their healthcare systems are heavily resource constrained and are experiencing significant problems in supplying healthcare services and also the people accessing these healthcare services (Top et al., 2020). The healthcare systems in SSA region lack proper health infrastructure or experience under-utilization of healthcare services. Wide spread extreme poverty, lower income per capita, higher income discrepancies and lower educational attainment coupled with poor quality governance all characterize developing economies (Top et al., 2020).

GDP, unemployment rate and Gini coefficient (income distribution) have been found to have a significant impact in health efficiency determination (Grigoli & Kapsoli, 2018).

Technical efficiency levels are heterogenous across healthcare facilities globally given evidence from several empirical studies that report varying technical efficiency levels for healthcare facilities. This is manifested in health system of France (Hadji & Degoulet, 2023), Germany (Vrabková & Lee, 2023), Kenya (Barasa et al., 2021), Iran (Mohamadi et al., 2022) and South Africa (Ngobeni et al., 2020) among others. Health promotion and response to the demands of people and community forms the major mission of the healthcare systems and in such a case hospitals have a special part to play as the major facilities for healthcare service provision (Mohamadi et al., 2022). These facilities are allocated resources and they are expected to convert them into healthcare outputs to meet the healthcare demands of the population. It is believed that despite the same healthcare resources provided to the facilities, it is common to find some facilities utilize the resources better than the others which brings about differences in levels of technical efficiency (Arhin et al., 2023).

In Uganda, studies have been conducted on technical efficiency among the healthcare facilities, such as; Ayiko et al., (2020) on general hospital technical efficiency, Ahimbisibwe, (2019) on resource utilization and technical efficiency among health center IV facilities and Tindimwebwa, (2018) on technical efficiency among health center II facilities among other studies**.** The general level public hospitals are largely experienced with allocative inefficiencies attributed to inefficiencies made during payments of employee benefits, purchase of drugs and costs on utilities (Ajanga, 2021). Geographical location, hospital size and Average Length of Stay (ALoS) of patients being some of the major determinants of technical efficiency among general hospitals (Ayiko et al., 2020).

Healthcare facilities in Uganda have also been found to operate at different levels of technical efficiency. Empirical studies reveal evidence of varying technical efficiency for hospitals in Uganda general hospitals (Ayiko et al., 2020). In South Western Uganda too, the empirical studies reveal differences in technical efficiency levels among healthcare facilities especially at lower level of healthcare service provision (Tindimwebwa, 2018).

Context of the Healthcare System in Uganda

Uganda's healthcare system like those of other developing countries, aims at achieving and sustaining good health for its people. The healthcare service centers in Uganda are mainly divided into public and private sector healthcare providers. The public and Private Not For Profits (PNFPs) are mostly higher levels of healthcare facilities while the Private For Profits (PFPs) majorly consists of lower levels health center (HCII) facilities and clinics (MOH, 2019). The public healthcare providers are designed in such a way to include at the top the national referral hospitals and regional referral hospitals. This is followed by the general hospitals, health center IV, III and II facilities and finally the village health teams (VHTs) (MOH, 2019). Furthermore, of the 6,937 healthcare facilities in Uganda, the public healthcare facilities form the biggest coverage of 45.16 percent while the community owned healthcare facilities make the least coverage of 0.10 percent (MOH, 2019).

According to National Development Plan (NDP) III, the health infrastructure network has recorded enhancement in the country namely; 2 national referrals, 19 regional referrals, a modern state of art women's hospital with a capacity of 320 beds that was opened in Mulago in 2018, heart and cancer institutes of Mulago hospital have also been expanded and improved, all which have increased access and utilization of healthcare services. The total expenditure per capita of 51 US dollars on healthcare financing is not only insufficient and inefficient, but also lower than the required 86 US dollars to achieve critical package of services in the background of universal health coverage (UHC). There is a growing burden of Non communicable diseases (NCDs) such as cardiovascular diseases, cancers with high mortality rate incidences surpassing existing health investments. Finally, the health worker to population ratio of 0.4 per 1000 which remains below the World Health Organization (WHO) suggested threshold of 2.5 medical staff per 1000 persons (NPA, 2020).

The key challenges facing the healthcare sector in include: low staffing levels especially in public which falls short by 29 percent and low budgetary allocations of about 7.2 percent. The health sector suffers from deficiencies in provision of dependable services, poor state of the facilities, malfunctioning equipment, inadequate medicines and supplies (UBOS, 2020). Furthermore, very few clients approximately 25 percent were satisfied with the quality of healthcare services provided by healthcare facilities in Uganda. The expectations of clients was not realized in close to 90 percent of the districts country wide, with the public healthcare facilities having the highest dissatisfaction score of 80 percent while private healthcare facilities standing at 63 percent (UBOS, 2020).

1.2 Statement of the Problem

Uganda considers its healthcare sector as one of the key strategic sectors to contribute to human capital development, in turn causing economic growth and development (Stefko et al., 2018). To enhance the performance and efficiency levels of the healthcare sector, the government of Uganda (GoU) has continued to put up infrastructural investments in the sector to meet the increasing healthcare demands from the public (NPA, 2020). Despite such enormous investments, the sector still suffers from a lot of inefficiencies especially in the public healthcare facilities (UBOS, 2020). Such inefficiencies manifest in the form of low levels of patient satisfaction and understaffing of health workers among public healthcare facilities (UBOS, 2020). Studies on hospital technical efficiency in Uganda reveal the following;

Ahimbisibwe (2019) indicates 72 percent TE existed in the health center IV (HCIV) facilities, while Ajanga (2021) reveals 29 percent allocative inefficiency prevailed in general hospitals. Ayiko et al., (2020) shows that constant returns to scale (CRS) TE in general hospitals was about 50, 49 and 53 percent for the respective financial years of 2012/13, 2014/15 and 2016/17. Although these studies focused on efficiency in healthcare facilities, they never focused on HCIII service providers. Moreover, these studies made no unanimous conclusion on the levels and determinants of technical efficiency, thus calling for additional investigations on efficiency in healthcare facilities in Uganda.

Although Tindimwebwa, (2018) reported that 72 percent TE existed in health center II facilities in South Western Uganda, his study didn’t not explore the determinants of the technical efficiency among health facilities in the region. Additionally, less is known about the technical efficiency in HCIII facilities in South Western Uganda. There still exists gaps on the levels of economic savings that would be achieved if inefficiencies were eliminated from inefficiency healthcare facilities. It is upon such a background that this study investigates the determinants of technical efficiency in South Western Uganda. Specifically, this study estimates the levels of technical efficiency and levels of economic savings as well as investigating the socioeconomic determinants of technical efficiency in the HCIII facilities in South Western Uganda.

1.3 Objectives of the Study

1.3.1 General Objective

To investigate the determinants of technical efficiency in the public HCIII facilities in South Western Uganda.

1.3.2 Specific Objectives

The study is guided by the following specific objectives;

(i) To estimate the different levels of technical efficiency in public HCIII facilities in South Western Uganda.

(ii) To establish the level of economic savings that can be achieved when technically inefficient facilities become technically efficient in South Western Uganda.

(iii) To examine the catchment population's socioeconomic determinants of technical efficiency in the public HCIII facilities in South Western Uganda.

1.4 Research Hypothesis

The research study was conducted basing on the stated hypotheses below;

i) Public HCIII facilities in South Western Uganda have the same level of technical efficiency.

ii) Economic savings and output augmentations improve on the technical efficiency for the technically inefficient public HCIII facilities.

iii) Catchment population's socioeconomic characteristics influence technical efficiency in public HCIII facilities in South Western Uganda.

1.5 Scope of the Study

1.5.1 Geographical scope

Geographically, the study focused on South Western Uganda specifically the Kigezi region. In this region the study covered six districts of Kabale, Kisoro, Kanungu, Rukungiri, Rubanda and Rukiga to investigate the determinants of technical efficiency in public HCIII facilities.

1.5.2 Content scope

The study focused on determinants of technical efficiency, the levels of technical efficiency in HCIII facilities in South Western Uganda, and the levels of economic savings. It also investigates socioeconomic determinants of technical efficiency among HCIII facilities in the South Western Uganda.

1.5.3 Time scope

The study mainly used the financial year of 2020/21 to capture the healthcare inputs received by HCIII facilities in South Western Uganda. In the same financial year, the study considered the outputs in the form of healthcare services.

1.6 Significance of the Study

The study is important to policy makers and researchers in the health sector as well as academic scholars in the following ways;

(i) Informing health sector of the levels and sources of technical efficiency and inefficiency among public healthcare facilities.

(ii) Informing the policymakers to reallocate resources among healthcare facilities so as to minimize resource wastage and achieve technical efficiency.

(iii) Making a significant addition to the existing literature about technical efficiency of public healthcare facilities in Uganda for academic and research reasons.

1.7 Organization of the Report

The rest of this report is organized as follows; chapter two presents the literature review, while the methodology is presented in chapter three. The results of the study are presented and discussed in chapter four. Chapter five highlights the summary, conclusion and recommendations from the study findings. This last chapter suggest areas for further research and the limitations of the study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviews both theoretical and empirical literature in line with the objectives of the study. It further presents the conceptual framework of the study. Specifically, theoretical literature on the concept of technical efficiency, the health production function and the socioeconomic determinants of technical efficiency of public healthcare facilities is covered. Empirical literature from the studies conducted in relation to the current study are also reviewed.

2.1 The Concept of technical efficiency

The concept of technical efficiency originates from Koopmans' 1951 definition which describes the input-output combination that is achievable such that output cannot be increased without increasing inputs given technology (Ahmed et al., 2020). It is further based on the ratio of output to input quantities of a production process. Consequently, any health decision making unit (DMU) attains its efficiency when it is able to operate along the corresponding production possibilities frontier (PPF) (Ali et al., 2017).

$$Technical\ Efficiency\ (TE) = \frac{weighted\ sum\ of\ health\ outputs}{weighted\ sum\ of\ health\ inputs} \ldots\ldots\ldots\ldots\ldots..(i)$$

The above equation (i) implies that technical efficiency can be computed by dividing the amount of healthcare outputs produced with a given number of healthcare inputs in the facility production process.

Analysis of efficiency in healthcare facilities is important as it helps to benchmark from those with better TE scores. In addition, it allows ranking of the facilities something which assists those performing poorly (i.e those with lower TE scores and ranks) to identify the gaps and thus able to correct such gaps (Ahmed et al., 2020). More so, studying the technical efficiency of complex DMUs, aids in accounting for the ability of these units to transform inputs into outputs. For comparison purposes it is vital to select homogenous DMUs (Agarwal, 2011). DMUs are usually described by the inputs they use and outputs they produce in such a way that both the inputs and outputs should be nonnegative (Charnes et al., 1978). Furthermore, technical efficiency concept originates from comparing the actual amount of outputs produced by a healthcare facility with potential amount of outputs that would have been produced at the optimal level through the hospital production process (Cavalcanti1, 2022).

2.2 Hospital production process

The study of health production process originates from Auster and the collaborator's first work of the analysis of the efficiency of the healthcare through the notion of a predictable production function whereby the environmental factors emerge as leading determinants of health outcome as per the study findings (Auster et al., 1969). A second analysis of production function was estimated by Grossman, (1972) who established a theoretical health production function whereby the socioeconomic, healthcare, lifestyle and environmental factors were regarded as inputs and health status as an output of the health production function key to note should be that hospitals form the critical element in a healthcare system due to the fact that it is the main provider for numerous healthcare services with the spending on medical care contributing the biggest fraction of healthcare expenditure (Gaynor & Town, 2011). The hospital production function thus provides insights into the understanding of the relationship between inputs and outputs of the hospital production function (Pproach et al., 2015).

2.3 Contextual literature review

In the analysis of hospital efficiency, the contextual factors such as number of healthcare facilities, location, population and population concentration or density in the catchment area, hospital beds are very paramount for this case (Mohamadi et al., 2022). Numerous studies have established a positive relationship between these contextual variables and hospital technical efficiency hence becoming very key for the national policy makers to take control of the factors to influence the healthcare facilities to become more technically efficient through healthcare resources allocation (Mohamadi et al., 2022).

2.4 Theoretical framework of technical efficiency

Owing to the earlier definition of technical efficiency, it is attained when a healthcare facility is producing along the frontier such that the available resources are used to obtain maximum outputs possible (Medarević & Vuković, 2021). Otherwise, below the production frontier, a facility operates technically inefficient due to excessive usage of resources (Bruning & Register, 1989). In the production of healthcare services, it is very uncommon to find DMUs operating in similar ways even when similar quantities and qualities of resources are provided. This implies variations in technical efficiency among the DMUs.

Two theories; property rights and agency theory have merged and dominated studies to explain variations in technical efficiency in the healthcare systems. The two theories uphold that discrepancies in efficiency emerge as a outcome of alteration in objectives, control behaviors between ownership and location, incentives and more so that make private institutions produce more efficiently compared to the public institutions (Christopher, 2106). Property rights and agency theory as further analyzed below;

2.4.1 Property rights theory of technical efficiency

This theory has been advanced to justify the differences in technical efficiency among DMUs. It builds on the fact that utility maximizing actions of a DMU behave in the side of maximizing financial and non-financial benefits in presence or absence of monitoring controls and incentives (Alchian & Demsetz, 1972). This theory argues that any efficiency destructing actions of a DMU are weakened to a significant degree in firms attempting to maximize profits since agent performance is likely to be noticeable and quantifiable which minimizes on the cases of shirking and other forms of non-productivity (Pauly et al., 1973; Bruning & Register, 1989).

With property rights view, non-profit hospitals are fundamentally inefficient as individuals hardly bond their economic performance to the firm. Additionally, non-profit hospital administrators end up pursuing other goals not cost minimization resulting into inefficiency (Pauly et al., 1973). Furthermore, in occasions where property rights are not well specified, the utilization and allocation of the property is bound to face misuses by everyone due to issues like shirking and free rider challenges yielding inefficiency (Tindimwebwa, 2018)**.**

2.4.2 Agency theory of technical efficiency

As a subdivision of game theory, Agency theory represents an economic procedure for analyzing and assessing the efficiency of firms (Magee, 2001). This theory involves a principal who employs and agent to act on his behalf, which agent chooses actions to maximize his utility under work averse assumptions in a way that tempting off the job opportunities may instigate him to re allocate his efforts to maximize his overall utility from both on and off job pays (Kunz & Pfaff, 2002).

This theory involves a best incentive binding agreement (contract) for a pay-for-performance that bonds the agent's pay off to production indicators which partly associate with his effort. In this manner, an agent trades off effort costs against the anticipated utility resulting from monetary and non-monetary costs in his decisions (Christopher, 2016). Finally the agency theory recommends rewarding agents basing on their performance that usually raise productivity, this theory represents methodology for comparing and assessing such contractual designs as their efficiency is concerned (Kunz & Pfaff, 2002).

2.5 Empirical literature

There is no consensus on a single factor that is entirely responsible for influencing the technical efficiency of healthcare facilities in Uganda, Africa and the world in general. Mixed findings are reported by several researchers (Barasa et al., 2021; Ahmed et al., 2020; Ayiko et al., 2020). This study therefore, reviews various empirical literature to obtain more insights into the determinants of technical efficiency in healthcare facilities.

2.5.1 Determinants of hospital technical efficiency

Provided with multiple resource inputs such as drugs, equipment and human resources, hospitals are not only the largest consumers of healthcare budgets but also producer facilities of healthcare services (Alsabah et al., 2020). The focus of decision makers is usually focused on the efficiency of these healthcare facilities in order to rationally allocate the resources to get maximum health outputs. Several studies have been conducted to evaluate the technical efficiency and establish determinants of efficiency in hospitals in Europe (Cepparulo & Giuriato, 2022; Han & Lee, 2021; Küçük et al., 2020). In Asia (Li et al., 2021; Chen et al., 2020; Liu et al., 2019). In Sub Saharan Africa (SSA) (Barasa et al., 2021; Fumbwe et al., 2021; Ngobeni et al., 2020; Babalola

& Moodley, 2020; Top et al., 2020). In Uganda (Ajanga, 2021; Ayiko et al., 2020; Ahimbisibwe, 2019; Tindimwebwa, 2018).

The findings show that technical efficiency of public hospitals is determined by institutional based factors such as size of the hospital, ownership, as well as environmental based factors such as socioeconomic qualities of the catchment population (Barasa et al., 2021; Alsabah et al., 2020; Ahmed et al., 2020; Ayiko et al., 2020). The complexity of allocation and utilization of resources amidst other variables that impact hospital efficiency remains a concern to examine which factors determine healthcare facility technical efficiency (Medarević & Vuković, 2021).

2.5.2 Economic savings from elimination of inefficiencies from healthcare facilities

The slack values present in inputs and outputs provide a basis to differentiate efficient healthcare facilities from inefficient ones (Agarwal, 2011). The best practicing facilities are identified and ranked first with TE score of 1.00 (100 percent) as the facilities maximizing outputs given the inputs (Valdmanis et al., 2008). Positive slack values indicate inefficiency implying employment of excess resources by the healthcare facility while negative values reveal inefficiency due to need to increase the inputs to achieve efficiency.

The identification of slack values aids healthcare facilities' planners of inefficient healthcare facilities to focus on the areas causing inefficiency so as to adjust appropriately to achieve technical efficiency by augmenting output given the fixed level of inputs at no additional cost (Ahmed et al., 2020). This can save the healthcare system by putting the scarce resources to maximum utilization to provide the best of healthcare services.

2.5.3 Socioeconomic determinants of technical efficiency

Despite classification of hospital efficiency determinants as institutional based and environmental factors, the utilization of healthcare services is highly reliant on socioeconomic factors (Alsubaie et al., 2016). Differences in the use of healthcare services have been attributed to variations in socioeconomic factors, whereby the vulnerable and poor individuals have been discriminated by healthcare providers (Alsubaie et al., 2016). Improving the socioeconomic status is understood to smoothen accessibility to healthcare services (Van Malderen et al., 2019). Furthermore, most of the efficiency literature stress that the hospital efficiency is not only influenced by internal factors but also external factors mainly environmental that are beyond the hospital management and control (Ahmed et al., 2020).

Studies have reported a positive relationship between health system technical efficiency and improved socio economic factors of the catchment population. Increased and fairly distributed income per capita of a nation, the status of being employed, improved access to good sanitation and clean water and high levels of literacy and education have been confirmed to significantly increase technical efficiency of health systems globally (Mbau et al., 2023).

This study reviewed related literature on socioeconomic determinants of technical efficiency of healthcare facilities as detailed below;

In an evaluation of a comparative efficiency of medical centers in Taiwan, Chiu et al., (2022) used a Dynamic DEA (DDEA) technique and an input orientation approach. Their findings show that population catchment significantly increased technical efficiency of the facilities. However, this has inconsistent findings in a way that public ownership is significant under variable returns to scale (VRS) efficiency but insignificant under constant returns to scale (CRS) efficiency. The study used input orientation which is basically used where facilities have control over resources yet in most times public medical facilities have less control over resources employed. They can only influence production of the health outputs, thus a limitation in the input orientation approach used in this study.

Barasa et al., (2021) explore the levels and determinants of technical efficiency using a sample of 47 healthcare systems in Kenya. They employ the DEA method with Simar and Wilson’s double bootstrap and bootstrap truncated regression. The results show that on average the healthcare system operated at 70 percent of technical efficiency. Development budget absorption, alcohol consumption, quality of care and population density significantly improved technical performance. HIV burden significantly reduced technical efficiency in the healthcare system facilities. Surprising private ownership was found to have no significant impact on the technical efficiency of the healthcare system which contradicts with economic theory as private ownership through profit orientation improves efficiency in production by minimizing costs on inputs. However, different results would come out using Tobit regression for private ownership and technical efficiency.

Ayiko et al., (2020) conducted an evaluation study on levels, trends and determinants of technical efficiency for a sample of 78 general hospitals in Uganda. The results revealed unstable trends for both CRS and VRS technical efficiency scores among Ugandan general hospitals overtime. The findings report CRS TE of 50, 49 and 53 percent and VRS TE of 61, 71 and 69 percent for the financial years of 2012/13, 2014/15 and 2016/17 respectively. Variables such as ownership of facility and Geographical location, significantly increased the technical efficiency of general hospitals overtime. Results further indicate that general hospitals in Western Uganda reported lower technical efficiency scores than those in the Northern region something that’s surprising basing on the findings by UNHS (2019) that reports least household poverty among households in the western Uganda at 19 percent against 31 percent for the households in Northern Uganda. This leaves many unanswered questions as to whether income levels are not significant in influencing technical efficiency. Additionally, the use of input orientation DEA technique is criticized on grounds of general public hospitals having less influence on health inputs but can control health outputs thus output DEA approach would have been appropriate for the study.

Ahmed et al., (2020) conducted a study on public district hospitals in Bangladesh using DEA input orientation and Tobit regression. The findings reveal an average CRS technical efficiency score of 79 percent which is highly attributable to high level of resource utilization in the district public hospitals in Bangladesh. The findings report population size, poverty head count as significant factors influencing technical efficiency among public hospitals. The main gap in this study is that given the fact that the study focused on public hospitals which hospitals are subject to resource constraints with minimum control as they are determined by the government, an output-oriented DEA approach would be suitable for the study rather than input orientation. Different results would therefore be obtained.

Küçük et al., (2020) using DEA model and a sample of 669 public hospitals to assess the technical efficiency of public hospitals in Turkey. Public hospitals operated at 83 percent technical efficiency. The results revealed that public hospitals in the southern location of Turkey were more efficient than in other regions of the country explained by the fact that less competition due to few private hospitals and the preference of the public hospitals by the people conditioned by the socioeconomic status in the region. The study didn’t not exhaust the difficulties of large size such as diseconomies of scale associated with managerial difficulties as indicated by economic theory.

Top et al., (2020), used a sample of 36 health systems while assessing the technical efficiency of African Countries using DEA approach. The study findings show that 58.33 percent of the systems were technically efficient. Number of physicians and hospital beds all expressed to 1000 people were found to significantly improve the technical efficiency while number of nurses per 1000 people and Gini coefficient reduced technical efficiency significantly. Largely the inefficiency among the health systems in Africa were associated to scale inefficiency. Critically, the study didn't consider major factors such as hospital ownership, population catchment area on technical efficiency of the health systems in Africa factors that are proved by majority studies to be significant in determining technical efficiency of health facilities.

Ahimbisibwe (2019), in his study investigated the level of utilization of resources among healthcare center (HCIVs) facilities using a DEA technique and a sample of 30 facilities to establish technical efficiency and its determinants. The results show that HCIVs were 72 percent technically efficient. The study findings though establish an insignificant effect of population density in the catchment area on technical efficiency of healthcare facilities unlike other studies that report significant effect. The current study therefore digs deeper to examine the effect of population catchment area on efficiency using latest dataset and an output-oriented DEA technique.

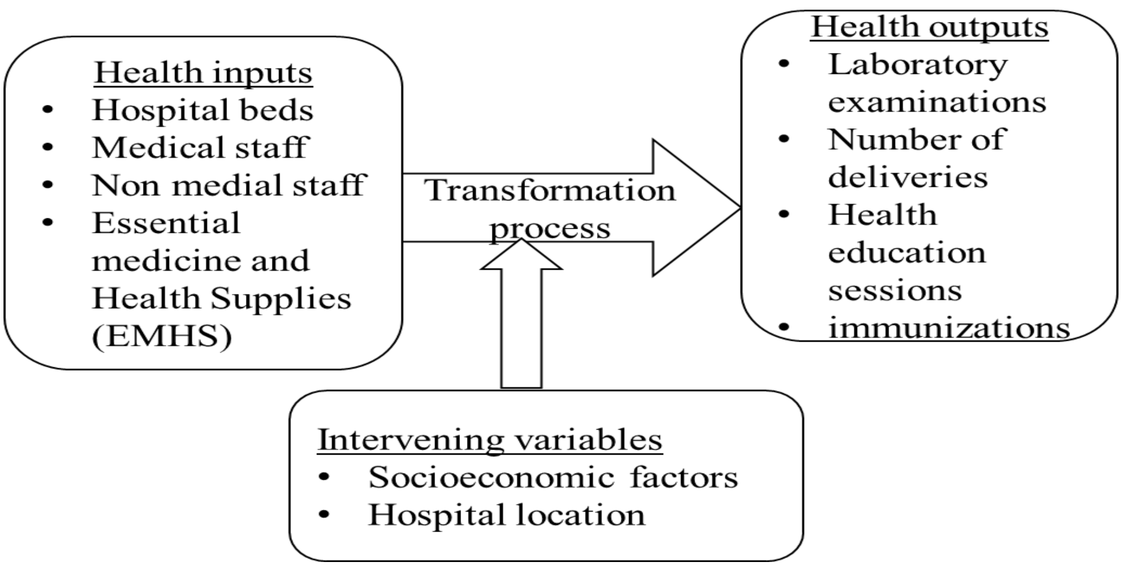
2.6 Summary of the Literature overview

Although studies have been conducted on technical efficiency of healthcare systems at a national, regional and global levels, there are gaps that have been cited in the reviewed literature. Most of the reviewed literature evaluate efficiency in developed economies yet this study focuses on technical efficiency in developing country. Most of the reviewed literature cover both private and public healthcare facilities yet this study concentrates on public healthcare facilities that are resource constrained. Some of the reviewed literature employed DEA input-oriented approach while this study uses output orientation DEA approach due to the fact that public healthcare facilities can influence outputs rather than the inputs. Finally, this study uses the latest socioeconomic variables to examine technical efficiency in health center III facilities in South Western Uganda and establish the level of economic savings that can be attained once inefficient health center III facilities attain efficiency.

2.7 Conceptual framework of the study

A conceptual framework gives direction of the study by providing the insights into the health production function of the health care facility.

A conceptual framework showing a healthcare facility transformation (production) process



Adopted from Tindimwebwa, (2018) and modified by the researcher

The healthcare facility (DMU) acquires healthcare resources such as medical staff (doctors, nurses and midwives), number of hospital beds, essential medical and health supplies (EMHS) and non-medical staff (accountants, counsellors) which it uses to obtain through a production process, healthcare outputs such as number of deliveries, immunizations, health education sessions and laboratory tests conducted in a year. The transformation (production) process is influenced by intervening variables such as socioeconomic factors and the location.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

This chapter discusses the research design used, data type and the various sources of obtaining the data, the model identification and description, and variables under the study. Sample size determination for the HCIII facilities, data management and analysis procedures are discussed in this chapter as well.

3.1 Research Design

The study adopted a cross-sectional descriptive research design focusing on various HCIII facilities as DMUs of healthcare services, given a set of health inputs used in the production of healthcare services. Various healthcare resources used by the healthcare facilities and healthcare outputs were quantified while capturing each HCIII facility as an individual DMU.

3.2 Data type and sources

The study used secondary data obtained from, whereby data on healthcare inputs and outputs were obtained from District Health Information Systems (DHIS-2) and District Planning Units (DPU) for the respective Local Governments. Data on socioeconomic characteristics for the population was mainly obtained from Uganda National Bureau of Statistics (UBOS). The respective sources are credible and trusted sources of data thus eliminating chances of biasness of the data used.

3.3 Sampling techniques.

The study adopted one of the common DEA principle of determining the sample size, it requires that the number of health facilities should be atleast three (3) times given the number of inputs and outputs for a facility as proposed Charnes (Charnes et al., 1978) and Banker (Banker et al., 1996). Letting the number of inputs be ***m***, number of outputs be ***k***, while the number of firms be **n**. There should be sufficient ***n*** in comparison with *m* and *k*, such that; $\mathrm{n} \geq 3(\mathrm{m}+\mathrm{k})$.

The study used four input variables namely; Medical staff, number of hospital beds, Essential Medical Health Supplies (EMHS) and number of nonmedical staff. Similarly, four output variables were used including; number of deliveries (Delv), laboratory services (Lab_serv), Health education sessions (HEdn_ses) and total number of immunizations (Immun) made a year. Thus, the sample size is determined as below;

$$n \geq 3(m+k), m = 4, k = 4.$$

$$n \geq 3(4+4)$$

$$n \geq 3(8)$$

$$n \geq 24$$

There are 53 public HCIII facilities in the sub region (MOH, 2019), from which a sample of 30 facilities was considered. The sample size is greater than 24 according to the DEA sampling principle. The 30 HCIII facilities were selected randomly following the criteria of population density in the catchment area that are served by the facilities. The table below shows the sample size determination for the facilities;

Table 3.1: Sample size determination for the facilities

Criterion	Description	Population size	Simple Random Sampling with PPS at r = 0.57
Below Mean (<10592)	Low population	11	6
10592 to 20,000	Moderate population	33	19
Above 20,000	High population	9	5
Total		53	30

Source: Researcher's own computations (2022)

Population mean of 10592 was used as a criterion for categorizing population such that "low population" for catchment areas with population below the population mean, "moderate population" for the catchment population between mean and 20,000 and finally for "high population" for catchment population above 20,000.

3.4 Sample criteria.

A three-stage sampling process was adopted in the study. This is explained as follows

3.4.1 Stratification. This formed the first stage of sampling where the HCIII facilities were stratified into three strata namely; low dense, moderate dense and dense population. This was guided by the population in the catchment area served by the facility.

3.4.2 Probabilistic sampling technique.

This formed the second stage of sampling. This involved determining probabilities for each stratum so as to determine the number of facilities from each stratum such that five (6) facilities were selected from low dense population, twenty (19) facilities were selected from moderately densely populated and lastly five (5) facilities from high dense population.

3.4.3 Simple random sampling technique.

This formed the third stage of sampling whereby each facility was assigned the same probability of being selected to avoid the selection bias. Thirty (30) facilities were hence forth selected and adopted as a sample size for the study as guided by the DEA sampling criteria of sample size being three times the summation of inputs and outputs.

3.5 Model description and specification

Studies have mainly employed both parametric (Stochastic frontier analysis) and non-parametric techniques (Data envelopment analysis) to analyze and measure the hospital efficiency (Hussain et al., 2022; Ahmed et al., 2020; Ayiko et al., 2020). This study adopts Data envelopment analysis (DEA) because of its strengths over SFA in a way that it is suitable for multiple inputs and outputs (Mujasi et al., 2016).

Data Envelopment Analysis (DEA) method is used in the first stage analysis for estimating the technical efficiency scores in various healthcare facilities (DMUs) and the estimation of slack values which is a basis for determining the levels of economic savings after improving the technical efficiency of inefficient facilities. Secondly, the Tobit regression model for establishing the significant socioeconomic factors for technical efficiency among the health facilities by regressing the socioeconomic factors as independent variables against the technical efficiency scores as dependent variable. The two models are detailed as below;

3.5.1 Data Envelopment Analysis (DEA)

DEA is a non-parametric linear programming model for a frontier analysis of multiple inputs and outputs of DMUs such as hospitals, developed by Charnes et al (Charnes Cooper Rhodes model) (Charnes et al., 1978), and extended by Banker et al (BCC model) (Banker et al., 1996). It is commonly used in relative efficiency evaluations in DMUs such as health facilities due to complexity relationship between inputs and outputs (Clement et al., 2008). Since early 1980s, DEA has been extensively used for efficiency analysis of health care systems.

DEA is described as “balanced benchmarking” that helps organizations test their assumptions about productivity (Ahmed et al., 2020). The major aim under technical efficiency is to minimize inputs but maximize output. DEA is highly appraised for the fact that DMUs can be ranked basing on the calculated efficiencies and hence the rankings can be used for selecting alternatives (Ahmed et al., 2020). Traditionally with DEA, each DMU is evaluated against the remaining DMUs through a portion of the sum of weighted outputs to the sum of weighted inputs, thereby distinguishing efficient units and the inefficient ones (Wu et al., 2013).

DEA has been highly employed in several studies for technical efficiency (Cepparulo & Giuriato, 2022; Cavalcanti1, 2022; Hussain et al., 2022). DEA is however, limited by failure to accommodate the socioeconomic and environmental factors in modelling for technical efficiency score as it only focuses on hospital inputs and outputs of the DMU (Smith & Street, 2005).

3.5.2 DEA specification

The study applied a DEA output-oriented constant return to scale (CRS) approach. CRS model assumes a production process in which the optimal mix of inputs and outputs is independent of the scale of operation (economies of scale) (Ngobeni et al., 2020). The objective function is to maximize the efficiency for the health facility subject to the resource constraints such that no health facility is more than 100 percent efficient (Clement et al., 2008). The output-oriented approach is justified on the grounds that the HCIII facilities receive and operate within the provided resources by the government and they have less or no control about them (resources). The resource inputs are predetermined at the district local government which is the immediate administrative level and at the ministry of health, the top most administrative level in the country (MOH, 2019).

The HCIII facilities therefore are supposed to provide efficient management and supervision so as to produce maximum possible health services (output) subjected to the given resources including medical staff, drugs, EMHS and support staff (non-medical) and any other inputs. This therefore provides the justification for using the output-oriented approach (Clement et al., 2008).

DEA model specification;

$$maximise: \quad \omega - \sum\left(\sum_{j=1}^{m} H_j^- + \sum_{r=1}^{k} H_r^+\right) \ldots \ldots \ldots \ldots (i)$$

Subject to;

$$\sum_{i=1}^{n} \theta_i \ X_{ij} + H_j^- \ = \ X_{i0}\,, \quad j = 1,2,\ldots,m \quad \ldots\ldots\ldots..(ii)$$

$$\sum_{i=1}^{n} \theta_i \, \gamma_{ri} - H_r^+ = \omega\gamma_{r0\,,} \ r = 1,2,\ldots,k \ \ \ldots\ldots(iii)$$

$\sum_{i=1}^{n} \theta_i = 1 \quad \ldots\ldots\ldots\ldots(iv), \quad \theta_i, H_j^-, H_r^+ \geq 0, \quad \forall\, i,j,r$

n = number of health facilities (HCIIIs), m = health resource input $\mathrm{HX_{ij}}$ $(\mathrm{j} = 1,2,\ldots,\mathrm{m})$,

$\omega =$ efficiency estimate, θ_i = positive scalars $(\mathrm{i} = 1,2,\ldots,\mathrm{n})$

$\mathrm{H_j^-}$ = excess of resource inputs, $\mathrm{H_r^+}$ = inadequaces of health care outputs

k = number of health resource outputs γ_{ri} $(\mathrm{r} = 1,2,\ldots,\mathrm{k})$

Such that any HCIII facility is regarded as most efficient if and only if $\omega^* = 1, H_j^- = H_r^+ = 0$, $\forall\, j,r$. Any facility that has an estimated value of less than one ($\omega^* < 1$), is considered to perform technically inefficient (Ahmed et al., 2020).

Adopted and modified from Tindimwebwa, (2018)

3.6 DEA model variables selection

3.6.1 Input variables

The variables selected were those that were commonly used in related studies. Number of hospital beds as a proxy for capital, number of medical and non-medical staff and the Essential Medical and Health Supplies (EMHS). Medical personnel as part of human resources play a vital role in health service delivery system; including medical doctors, nurses, midwives (Şahin & İlgün, 2019). The Essential Medicines and Health Services (EMHS) forms the biggest expenditure in the Ugandan health sector after human resources hence vital among the hospital inputs (Ministry of Health, 2018).

3.6.2 Output variables

The healthcare facilities as decision making units' employ healthcare resources to produce healthcare outputs. The considered output variables were; number of deliveries made at the facility by expectant mothers, immunizations, laboratory tests and services and number of health education sessions conducted by a facility in a year. The selected variables were used in assessment of efficiency of health care facilities in Sub-Saharan Africa (Babalola & Moodley, 2020) and in Saudi Arabia while studying socioeconomic factors of patient's health resource utilization (Alsubaie et al., 2016) and in Cameroon while estimating efficiency of public hospitals (Christopher, 2016).

Table 3.2: Showing variable description for the DEA model.

Input variables	**Variable description**
Hospital beds	Total number of beds representing capital of a healthcare facility.
Medical personnel	Total number of doctors, nurses and midwives employed in the facility.
Non-medical staff	Total number of fulltime or equivalent researchers, social workers, logistic workers.
Essential medicines and health supplies (EMHS)	Funds spent on purchase of medicines and other health supplies for the healthcare facilities by the ministry of health in Uganda.
Output variables	
Number of deliveries	Total number births made and recorded at the facility in a year.
Laboratory services	Total number examinations and tests conducted using laboratory

(tests)	equipment by a facility in a year.
Immunizations	Total immunizations recorded at a facility in a year.
Health education sessions	Total sensitization sessions conducted by a facility to educate the public on health matters.

Source: Researcher's own tabulation (2023)

3.7 Socioeconomic factors for technical efficiency and tobit regression

3.7.1 Regression variables

The study considered the socioeconomic characteristics of the population that receive the healthcare services from the public health center facilities. The selection of these variables was guided by previous conducted studies and were found to have a significant impact on technical efficiency. The factors considered for the study are provided in the table below with their description together with expected signs.

Table 3.3: Socioeconomic characteristics of population surrounding the facility.

Variable	Description	Expected sign
Income	Average annual income earned by the patient receiving treatment at the facility.	+
Unemployment rate	The percentage of the jobless population in the facility catchment area	+/-
Catchment population in South	Total number of people in the catchment area served by a facility in a year.	+/-

Western Uganda		
Infectious diseases	Total number of patients treated from infectious diseases in a year	+
Age <5	Patients below the age of 5 receiving treatment in a year	+
Age > 65	Patients served above 65 years in a year	-
Household size	Average number of people in a family within the catchment area	+
Location	A dummy variable for location of the facility, Urban =1, otherwise=0	+/-
Competition	Competition among the facilities measured by number of private health facilities in the catchment area of the HCIII facility	+/-

Source: Researcher's own tabulation (2023)

3.7.2 Tobit Regression model

Developed in 1958 by Tobin, the tobit model suits the regression for the dependent variable that is censored or constrained to a certain range of values (Alatawi et al., 2020a). DEA technical efficiency scores were used as dependent variable while the socioeconomic factors used as explanatory variables respectively in this regression. A number of studies on technical efficiency have used tobit model to estimate the efficiency scores among hospitals such as; (Lupu & Tiganasu, 2022; Barasa et al., 2021; Küçük et al., 2020; Alsabah et al., 2020). The efficiency scores range between 0 and 1 for most inefficient and most efficient DMU respectively, making it a censored variable which qualifies the use of tobit regression while disqualifying ordinary least squares regression (Lupu & Tiganasu, 2022; Ahmed et al., 2020).

Tobit model regression analysis follows the following specification;

$$Y_i^* = \beta_0 + \beta_i X_i + \varepsilon_i$$

Considering the socioeconomic factors under the study, the tobit regression becomes;

$$Y_i{}^* = \beta_0 + \beta_1 lnInc\ + \beta_2 Un_{rate} + \beta_3 Cat_{Pop} + \beta_4 Infect + \beta_5 Age < 5 + \beta_6 Age > 65 + \beta_7 HHsize + \beta_8 Loc + \beta_9 Comp + \varepsilon_i.$$

Whereby $0 \leq Y_i^* \leq 1$,

β_0 *is th intercept,* β_n *measures the coefficients of the regression* , ($n = 1,2,3 \ldots ,8$)

$Y_i{}^*$ *is the efficiency score,* ε *caters for the disturbances in the model.*

lnInc implies income levels (log transformed), Un_rate measures unemployment rate, Cat_Pop population in the catchment area, $Infect$ for infectious diseases among population, $Age < 5$ measures patient population below the age of 5, $Age > 65$ is for patient population above 65 years, $HHsize$ represents household size**,** Loc represents location of the facility**,** *Comp* means competition among healthcare facilities in the region.

The joint effect of the parameters was tested to establish their significant effect in determining variations in technical efficiency across facilities.

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0$ for no joint significant effect on efficiency determination.

$H_A: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq \beta_8 \neq \beta_9 \neq 0$ was tested using F-statistic test. Thus, the overall model was significant in explaining the technical efficiency variations among the HCIII facilities.

3.8 Ethical considerations

An introductory letter was obtained from the Head of Department of Economics, Kyambogo University verifying the researcher as a student of graduate program doing research as a requirement for the attainment of the award of a Master degree of Arts in Economics. The letter was presented to relevant District Local Government (DLG) authorities in the area of study to obtain the data from relevant offices.

3.9 Data management and analysis

3.9.1 Management of data

Data was obtained from Uganda Bureau of Statistics (UBOS), District Health Information System (DHIS) and respective District Planning Units (DPUs) for the financial year 2020/21 were entered in Microsoft excel software capturing both input and output variables and after which was imported to Stata software version 15 for analysis. The input and output variables were entered in Microsoft excel software and a database created for analysis. Data coding, sorting, cleaning and other data procedures were performed.

3.9.2 Data Analysis

Data envelopment analysis (DEA) program a linear programing technique which is imbedded in Stata software version 15 was used to estimate the technical efficiency scores of various healthcare facility decision making units. The slack values were also estimated to establish the levels and sources of inefficiency in healthcare facilities. Tobit regression analysis was performed using the same software stata version 15, the results were analyzed at 10 percent level of significance. The unit of analysis for the study was a health center (HCIII) facility.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND INTERPRETATION OF THE FINDINGS.

4.0 Introduction

This chapter mainly presents the descriptive statistics, TE scores, correlation coefficients are presented. The level of economic savings and output augmentations are analyzed. Socioeconomic determinants of technical efficiency are also discussed in this chapter.

4.1 Descriptive statistics for input and output variables

The descriptive statistics cover the mean, standard deviations, the maximum and minimum values for both input and output variables under the study for 30 Health Centre III facilities for the financial year of 2020/21. Input variables include number of beds as proxy for capital, medical and non-medical staff for human resources, and expenditure on drugs and supplies (EMHS) while immunizations, number of deliveries, laboratory tests and health education sessions were outputs considered for the study. They are presented in the **table 4.1** below.

Table 4.1: Showing descriptive statistics for the input and output variables.

Variable	Obs	Mean	Std. error	Min	Max
Input					
Beds	30.0	14.4	1.4	2.0	35.0
Med_Staff	30.0	12.4	0.7	5.0	20.0
EMHS	30.0	110000000.0	20630883.0	22400000.0	278000000.0
N_MedS	30.0	3.7	0.2	2.0	6.0
Output					
Deliv	30.0	204.4	22.1	22.0	441.0
Lab_Serv	30.0	3717.4	639.6	300.0	18441.0
HEdn_ses	30.0	96.4	69.3	0.0	2103.0
Immun	30.0	1977.4	375.2	46.0	8732.0

Source: Researcher's own computation (2023)

Given 30 Health Centre III facilities under the study, the results in Table 4.1 above, show that the average number of hospital beds were 14, with about 12 medical and 4 non-medical staff with each facility receiving Essential Medicines and Health Supplies (EMHS) worth 110 million shillings on average. The standard errors recorded among the input variables were; 1.4 beds, 0.7 medical staff, 0.2 non-medical staff and about 20,630,883 million shillings for EMHS. The highest number of beds were 35 against a minimum of 2 beds, 278million was the highest compared to 22.4million the lowest, while 20 medical staff were the highest number employed in a facility against a minimum of 5. The highest number of employed non-medical staff was 6 compared to a minimum of 2. Big discrepancies (maximum and minimum) are observed among the input variables across the facilities, which could partially be justified by the fact that some facilities have existed for many years compared to newly established facilities implying differences in scale/size of operations.

On average, about 204 deliveries, 3717 laboratory services (tests), 96 health education sessions and 1977 immunizations were recorded by the public health facilities for the financial year 2020/21 in sub region. The standard errors among the output variables recorded were; 22.1 for deliveries, 639.6 for laboratory services (tests), 69.3 health education sessions and 375.2 immunizations. Furthermore, the results indicated that maximum deliveries of 441 and minimum of 22, 18441 maximum laboratory tests were conducted with a minimum of 300 tests. Some facilities didn’t conduct health education sessions while a maximum of 2103 sessions were conducted. Finally, immunizations were conducted 8732 highest with 46 being the lowest.

4.2 Estimation of Technical Efficiency (TE) scores for the HCIII facilities

Majority of the empirical studies have used the Data Envelopment Analysis (DEA) technique to analyze TE levels among various health facilities in Uganda, Africa and Globally. DEA technique is highly preferred given its ability to accommodate multiple input and output variables and less concentration on the functional form specification (Babalola & Moodley, 2020).

The TE scores can be categorized basing on a scale of range into; low efficiency (0.0 to 0.50), medium efficiency (0.51 to 0.80), high level of efficiency (0.81 to 0.99) and finally most efficient (1.0), (Cavalcanti1, 2022). The TE scores for various facilities are presented in the table below;

Table 4.2: Technical Efficiency results and the benchmarks for the respective health facilities

S/N	DMU	Rank	TE Score	CRS_TE	VRS_TE	SCALE	RTS	BENCH_M	Ω
1	DMU37	28	0.2167	0.2167	0.2167	1.0000	0.0000	DMU34	0.0623
2	DMU4	1	1.0000	1.0000	1.0000	1.0000	0.0000		
3	DMU43	26	0.2884	0.2877	0.2884	0.9974	1.0000	DMU34	0.0629
4	DMU42	27	0.2491	0.2431	0.2491	0.9759	1.0000	DMU34	0.1487
5	DMU39	16	0.8403	0.8335	0.8403	0.9919	1.0000	DMU26	0.5862
6	DMU44	29	0.2100	0.2095	0.2100	0.9979	1.0000	DMU34	0.0576
7	DMU2	30	0.0892	0.0858	0.0892	0.9622	1.0000	DMU21	0.0367
8	DMU53	24	0.3632	0.3570	0.3632	0.9829	1.0000	DMU51	0.1568
9	DMU41	15	0.8602	0.5615	0.8602	0.6528	1.0000	DMU34	0.4636
10	DMU29	1	1.0000	1.0000	1.0000	1.0000	0.0000		
11	DMU38	25	0.3022	0.2994	0.3022	0.9908	1.0000	DMU34	0.2116
12	DMU34	1	1.0000	1.0000	1.0000	1.0000	0.0000		
13	DMU51	1	1.0000	1.0000	1.0000	1.0000	0.0000		
14	DMU10	1	1.0000	1.0000	1.0000	1.0000	0.0000		
15	DMU15	1	1.0000	1.0000	1.0000	1.0000	0.0000		
16	DMU33	19	0.6443	0.6282	0.6443	0.9749	1.0000	DMU15	0.3665
17	DMU1	23	0.4529	0.4469	0.4529	0.9869	1.0000	DMU7	0.1562
18	DMU40	17	0.7313	0.7148	0.7313	0.9774	1.0000	DMU34	0.6778
19	DMU7	1	1.0000	1.0000	1.0000	1.0000	0.0000		
20	DMU20	20	0.6374	0.6192	0.6374	0.9714	1.0000	DMU7	0.1889

21	DMU26	1	1.0000	1.0000	1.0000	1.0000	0.0000		
22	DMU25	21	0.5964	0.5404	0.5964	0.9060	-1.0000	DMU27	0.4165
23	DMU22	22	0.5650	0.5650	0.5650	1.0000	0.0000	DMU21	0.4425
24	DMU28	18	0.6752	0.6674	0.6752	0.9884	1.0000	DMU26	0.3385
25	DMU45	1	1.0000	1.0000	1.0000	1.0000	0.0000		
26	DMU27	1	1.0000	0.9689	1.0000	0.9689	-1.0000		
27	DMU23	1	1.0000	1.0000	1.0000	1.0000	0.0000		
28	DMU17	1	1.0000	1.0000	1.0000	1.0000	0.0000		
29	DMU21	1	1.0000	1.0000	1.0000	1.0000	0.0000		
30	DMU18	1	1.0000	1.0000	1.0000	1.0000	0.0000		
		Mean	0.7240	0.7082	0.7240	0.9775			
		Std.Dev.	0.3151	0.3165	0.3151	0.0643			
		Min	0.0890	0.0860	0.0890	0.6530			
		Max	1.0000	1.0000	1.0000	1.0000			

Source: Researcher's own computation (2022). DMU names attached in the appendix.

Practically, TE scores vary from 1.000 (100percent) for most efficient to 0 (0 percent) for not efficient completely. Employing CRS and output orientation model, the findings indicate that of the total 30 DMUs under the study, about 14 DMUs (47 percent) operated at the highest frontier with the TE score of 1.000 (100 percent) thus ranking 1st. This implies that the facilities used optimally the availed health resources to produce maximum health outputs thus operating technically efficient. The average TE score is 72 percent, with a minimum of 9 and maximum of 100 percent.

Some levels of technical inefficiency are cited among facilities represented by technical efficiency scores of less than 1. The least technically efficient facility is DMU2 which is about 9 percent technically efficient, ranking 30th and most less performer among facilities under the study. Other DMUs in the least performing ranks of 29th, 28th, 27th, 26th and 25th were; 44(21), 37(22), 42(25), 43(29) and 38(30), TE scores are indicted in the parentheses in percent. This implies that the less efficient facilities would be become efficient by properly utilizing health resources by 91, 79, 78, 75, 71 and 70 percent respectively from the 30th to 25th ranked facilities respectively. Furthermore, other DMUs operated relatively at a moderate level of technical efficiency above 50 percent but less than 100 percent. These include; 41(86), 39(84), 40(75), 28(67) and 33(64), considering percent in the parentheses for TE scores.

Discussion of the technical efficiency results

The study findings reveal that the healthcare facilities were on average 72 percent technically efficient. This implies that the health facilities (DMUs) needed to improve resource allocation and utilization to increase health output and improve on their technical efficiency by 28 percent. These findings are in agreement with other related studies that have been conducted on technical efficiency, reporting variations in technical efficiency levels among hospitals. The average technical efficiency score in this study is similar to 72 percent (Tindimwebwa, 2018), but slightly above 69 percent (Ayiko et al.,2020) reported in previous technical efficiency studies for Ugandan healthcare facilities. The efficiency score results in this study are however slightly less than 76 percent for Saudi Arabia (Alatawi et al., 2020a), slightly higher than 70 percent for Kenya (Barasa et al., 2021), although less than 79 percent for Ethiopia (Ali et al., 2017) and 93 percent for China (Chen et al., 2020), 80 percent for Kenya (Ojwang OYIEKE et al., 2021), 87 percent for South Africa (Ngobeni et al., 2020).

The intuition is that there is heterogeneity among public health facilities in health service production and provision even when provided with similar resources, they operate different levels of technical efficiency. Precisely some facilities successfully convert inputs to come up with maximum level of output compared to others**.**

Scale efficiency scores

The scale efficiency (SE) scores determined as a ratio of CRS TE to VRS TE show efficiency due to size and scale of operation of a facility. A facility is scale efficient when its size of operation is optimal so that any modifications on its size renders it less efficient. Scale inefficiency reflects healthcare resource wastages attributed to size of the facility. Returns to scale (RTS) is useful in this case as it shows the level of scale inefficiency associated with the respective DMU.

The study results show that 15 (50 percent) of the 30 studied DMUs (healthcare facilities) were associated with constant returns to scale meaning that they were scale efficient and so they operated at their optimal size. Any attempt to increase their size beyond the current one, would make the facilities too large which may render them scale inefficient due to diseconomies of scale. Whereas 13 DMUs (43 percent) were associated with increasing returns to scale, an implication that these facilities produced the healthcare outputs at a proportion high than the proportion of healthcare resources. Only 2 DMUs (07 percent) were associated with decreasing returns to scale (DRS) which implies that a proportionate increase in healthcare resources is associated with a proportionate fall in healthcare outputs produced by a facility. The average scale efficiency is 98 percent with a minimum of 65 and a maximum scale efficiency of 100 percent.

Discussion of the scale efficiency scores

The results of this study show an average scale efficiency score of 97.7 percent. This means that the healthcare facilities would improve on scale efficiency by 2.3 percent given the healthcare resources. The implication is that most of the healthcare facilities operated close to the scale efficiency score of 100 percent. The variations in efficiency due to size was therefore very minimal as most of the facilities operated near the optimal size.

Upon comparison with previous studies in Uganda, the average scale efficiency scores are however slightly less than 99 percent (Tindimwebwa, 2018), though bigger than 70 percent (Ayiko et al., 2020). In relation to other studies, this average scale efficiency score is slightly higher than the mean scale efficiency scores of 89 percent in Kenya (Ojwang OYIEKE et al., 2021), 73 percent in Tanzania (Fumbwe et al., 2021) and 87 percent in Ethiopia (Ali et al., 2017), 82 percent for Saudi Arabia (Alatawi et al., 2020b).

Benchmarking for the healthcare facilities

Inefficient healthcare facilities can improve on technical efficiency levels by benchmarking to emulating the practices from the efficient healthcare facilities. From the findings in **Table 4.2**, the respective efficient DMUs to be benchmarked by corresponding less efficient ones guided by the weights for benchmark represented by omega (Ω) generated under DEA software. Focusing on the study findings, DMU34 is the most benchmarked healthcare facility by several DMUs (health care facilities); 37 (0.062), 43 (0.063), 42 (0.149). All benchmarked DMUs operate 100 percent technical efficient implying optimum healthcare resource utilization to produce maximum healthcare output. Benchmarking helps to make less efficient DMUs more efficient by adopting better practices from most efficient ones.

The study findings are in line with other studies on technical efficiency which recommend benchmarking of inefficient healthcare facilities to improve on their technical efficiency. Previous studies in Uganda reveal that inefficient healthcare facilities would improve their technical efficiency scores by benchmarking from efficient ones (Tindimwebwa, 2018; Ayiko et al., 2020) and in South Africa (Ngobeni et al., 2020), and Saudi Arabia (Alatawi et al., 2020b).

4.3 Estimating the level of Economic saving from healthcare input reductions and output augmentations by inefficient facilities

Basically, technical inefficiency is associated with inability to optimally utilize the available healthcare resources. This means that there is some level of economic savings that can be attained after improving the efficiency of inefficient facilities (HCIII). The DMU can reduce healthcare resource while maintaining the level of healthcare outputs or maintain the level of healthcare resources while augmenting the healthcare outputs to improve on its efficiency technically (Valdmanis et al., 2008). The economic savings are indicated by the amount of healthcare resource reductions made once the inefficient facilities attain technical efficiency as shown by the slack values in **table 4.3** below;

Table 4.3: Slack values for healthcare inputs and output variables

Input slacks						Output slacks			
SN	**DMU**	**Beds**	**Med_Stf**	**EMHS**	**N_MedS**	**Delv**	**Lab_Svcs**	**Immun**	**HEdn_ses**
1	DMU37	0.000	0.770	4.0E+07	0.000	19.364	0.000	19.791	0.000
2	DMU4	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
3	DMU43	0.000	0.000	5.0E+07	0.000	15.531	1394.540	0.000	0.000
4	DMU42	0.847	0.000	2.4E+07	0.000	42.534	2745.000	0.000	0.000
5	DMU39	0.000	3.803	1.7E+08	0.000	0.000	0.000	5.579	0.000
6	DMU44	0.000	0.000	3.5E+07	0.451	0.000	0.000	0.000	0.000
7	DMU2	0.000	0.306	2.3E+05	0.211	0.000	0.000	20.016	0.000
8	DMU53	0.000	0.000	6.5E+05	0.181	3.239	176.902	0.000	0.000
9	DMU41	14.623	4.893	1.0E+08	1.257	0.000	7788.380	0.000	7.555
10	DMU29	0.000	0.000	3.0E-08	0.000	0.000	0.000	0.000	0.000
11	DMU38	0.000	0.000	1.9E+07	0.190	0.000	952.366	0.000	0.000
12	DMU34	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
13	DMU51	0.000	0.000	4.3E-09	0.000	0.000	0.000	0.000	0.000
14	DMU10	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
15	DMU15	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
16	DMU33	0.000	1.442	1.6E+07	0.000	0.000	2511.390	0.000	14.971
17	DMU1	0.000	0.000	0.0E+00	0.000	0.000	71.013	0.000	0.617
18	DMU40	7.319	1.875	1.4E+07	0.050	0.000	9139.830	0.000	0.000
19	DMU7	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
20	DMU20	0.000	0.000	3.2E+06	0.854	0.000	0.000	0.000	0.000

21	DMU26	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
22	DMU25	0.888	1.062	7.6E+06	0.000	0.000	712.005	0.000	0.000
23	DMU22	0.000	0.000	1.4E+06	0.576	0.000	293.580	3.191	11.293
24	DMU28	0.000	0.000	3.2E+06	0.657	0.000	0.000	0.000	0.000
25	DMU45	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
26	DMU27	0.000	0.000	4.9E-08	0.000	0.000	0.000	0.000	0.000
27	DMU23	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
28	DMU17	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
29	DMU21	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000
30	DMU18	0.000	0.000	0.0E+00	0.000	0.000	0.000	0.000	0.000

Source: Researcher's own computation (2023). DMU names are attached in the appendix.

Any DMU with slack values is termed technically inefficient, otherwise it is technically efficient. Observations have to be made for both efficiency scores and slack values while analyzing TE for DMUs. The sources and amount of inefficiency in the DMU is indicated by the non-zero slack values. Furthermore, an inefficient DMU can be made more efficient by projection onto the frontier with improvements achieved through proportion reduction in healthcare resources. Important to note is that TE is fully achieved if and only if the slack values are equivalent to zero (Agarwal, 2011).

Of the 30 DMUs, the results reveal that 14 (47 percent) were technically efficient hence had no slack values for both input and output variables. They included; DMUs such as; 4, 29, 34, 10, 51, 15, 7, 26, 45, 23, 17, 21, 27 and 18. They had TE score of 1.00 meaning they utilized the healthcare resources optimally to get maximum healthcare output. The remaining 16 (53 percent) had slack values implying technical inefficiency. Whereas the input slack values represent the amounts that need to be reduced or taken away from the DMU, the output slacks show the amount of output augmentations to enable a DMU operate efficiently.

Considering the least technical efficient DMUs, DMU2 (9 percent) can operate at the frontier by reducing EMHS amounting to 23million and increasing the immunization by 20. By reducing EMHS amounting to 34.9million, and about one nonmedical staff, DMU44 can attain the highest TE score (100 percent). DMU37 can improve on its technical efficiency by reducing on medical staff by one, 40million EMHS while augmenting outputs by 19 deliveries and 20 immunizations. Additionally, DMU41 needs to reduce inputs by 15 beds, 5 medical staff, one non-medical staff and 101million EMHS while augmenting health outputs by 7788 deliveries and 8 health education sessions to operate at the highest frontier hence becoming technically efficient, references be made to table 4.3 above.

Discussion of the economic savings and output augmentation results

The study findings show that reduction in number of hospital beds would improve technical efficiency among healthcare facilities in the region. These findings are in agreement with the findings in similar studies. In Tanzania, a study on technical efficiency among public hospitals revealed that reducing number of beds employed in each hospital by two (2) beds would enable less efficient hospitals become more efficient (Fumbwe et al., 2021). Similarly, Alatawi et al., (2020) indicate that reducing the number of beds by 48 beds would enable hospitals become more efficient in Saudi Arabia. Additionally, Alsabah et al., (2020) concluded that a reduction in number of beds by 602 beds would enable hospitals become more technically efficient in Kuwait. Reducing number of beds on average by 9 would increase technical efficiency among hospitals in Ethiopia (Ali et al., 2017).

In this study, the findings show that a reduction in medical staff would result into technically inefficient facilities become more technically efficient. The findings are in agreement with findings established in other similar studies on technical efficiency among healthcare systems such as; Alsabah et al., (2020), revealed that hospitals would become more technically efficient by reducing 9.7 and 8.2 percent for doctors and nurses respectively in Kuwait. Similarly, Fumbwe et al., (2021), revealed that hospitals would become technically efficient by reducing the number by 3 doctors, 11 medical attendants and 5 nurses in Tanzania. In south Africa, Ngobeni et al., (2020), in their study revealed that hospitals would become technically efficient after reducing the health staff by 17000 people, as this was believed to reduce spending on health staff and the saved funds would be used to refurbish but also establish more hospitals which would put low the pressure on the public health system.

The findings in this study show that the technical efficiency would be improved among less technically efficient facilities by reducing the expenditure on essential drugs and health supplies (EMHS) as this could save money which would be reallocated for other relevant hospital inputs. The findings are in agreement with the findings in related technical efficiency studies. Ngobeni et al., (2020), in their study reveal reducing health expenditure by R17 billion would result into improvement in technical efficiency in the regional hospitals in South Africa. In Ethiopia reducing expenditure on drugs would improve on technical efficiency among hospitals (Ali et al., 2017).

The study findings also show that technical efficiency would be improved by reducing the number of non medical staff employed in the facilities. This is in the same view with the findings by Alsabah et al., (2020), that show that a reduction in non medical staff by 7.1 percent would enable technically inefficient hospitals improve on technical efficiency levels in Kuwait.

Similarly, in their study findings, Chen et al., (2020), show that reduction of other hospital technical staff by 4996 and 357 in Beijing and Hebei provinces of China respectively would improve technical efficiency.

The findings in the present study indicate that technical efficiency levels would be improved by augmenting the health outputs among the facilities.

Increasing laboratory tests conducted by health facilities would help to improve on technical levels among inefficient health facilities. The study findings are in line with other study findings. Alatawi et al., (2020), in their study show that augmenting laboratory tests by 66107 tests would help to improve technical efficiency among hospitals in Saudi Arabia. Similarly, increasing laboratory tests and services offered by 53 percent would help to improve on technical efficiency among hospitals in Kuwait (Ahmed et al., 2020).

The study findings reveal that inefficient health facilities can improve their technical efficiency levels by increasing on the immunization visitations conducted. The findings are in line with other related study findings such as in Burkina Faso, where increasing the number of immunizations by 28 percent would help to improve on the efficiency levels of less efficient hospitals (Marschall & Flessa, 2009). In Benin, increasing immunization levels was also thought to improve on technical efficiency among hospitals (Emrouznejad & Makoudode, 2007). Similarly increasing the immunization among children under five years by 36.43 would help to improve technical efficiency among hospitals in Ethiopia (Ali et al., 2017).

The findings in this study also show that inefficient facilities can boost their technical efficiency by augmenting the health education sessions. Behavioral patterns would improve through increased health education sessions by utilizing the underutilized services. Similar findings were established in a study by Ali et al., (2017) which indicate that increasing health education sessions by 59.12 would increase technical efficiency among inefficient hospitals in Ethiopia. In Benin, a study by Emrouznejad & Makoudode, (2007) also indicate that increasing health education sessions would help improve on technical efficiency levels among hospitals.

The findings in this study reveal that increasing the number of deliveries at the health facilities can help to improve technical efficiency among inefficient health facilities. The findings are in line with the findings in the study conducted by Marschall & Flessa, (2009), which show that increasing deliveries by 79 percent would help improve on technical efficiency among inefficient hospitals in Burkina Faso. Similarly in Benin, increasing the number of deliveries would help improve technical efficiency among inefficient hospitals (Marschall & Flessa, 2009).

4.4 Socioeconomic determinants of Technical Efficiency among HCIII facilities

The study investigated the socioeconomic factors based on the patient's qualities to determine which factors significantly influenced TE of public healthcare facilities. The influencing variables or factors were selected basing on common socioeconomic determinants employed by technical efficiency studies carried out by several scholars. Average annual income levels, unemployment rate, catchment population, infectious diseases, age below 5 (children), age above 65 (elderly), household size, competition and location were employed in the analysis. Similar variables were used while analyzing socio economic factors for utilization of primary health care in Saudi Arabia (Alatawi et al., 2020a) in Bangladesh (Ahmed et al., 2020). Descriptive statistics, correlation coefficients, Tobit regression and the discussion of the results are all analyzed below;

Table 4.4: Descriptive statistics of the Socioeconomic factors

Variable	Obs	Mean	Std. error	Min	Max
TE score	30	0.72	0.06	0.09	1.00
Inco	30	593467.70	58146.28	176770.00	1440000.00
Un_rate	30	31.00	3.47	1.00	72.00
Cat_Pop	30	12508.04	1786.85	1120.00	36308.00
Infect	30	2048.27	489.48	5.00	9691.00
Age<5	30	1927.00	245.82	192.00	5119.00
Age>65	30	868.57	304.36	16.00	8842.00
HHsize	30	4.87	0.19	3.00	8.00
Comp	30	2.97	0.47	0.00	12.00
Categorical variable		Freq	Percent		
Loc	Rural	16	53.33		
	Urban	14	46.67		
		30	100.00		

Source: Researcher's own computation (2023)

The average technical efficiency score of the facilities in the sub region was 0.72 implying that about 72 percent of the facilities were technically efficient. The worst facility operated at about 9 percent compared to the most efficient facility that operated at fully capacity 100 percent.

The annual average income is of 593,500 with the standard deviation of 318,500. An earned maximum of 1,440,000 whereas 176,770 is the lowest annual income received (Ug. shillings).

About 31 percent of the population that accessed healthcare services from the health facilities were unemployed, with the unemployment rate ranging between 72 percent and 10 percent for highest and lowest respectively among the patient population.

On average, about 1927 and 867 patients served by the facilities were below five (<5) years and above sixty-five (>65) years respectively. More than a half of the facilities were situated in rural setups (53.33 percent) while the remaining facilities (46.67 percent) were located in urban areas.

On average, each house hold consisted of 5 members with 3 members being the least size of a household unit while a maximum of 8 members stayed together.

About 3 private healthcare facilities were located near the public facility. However, some of the HCIII facilities hardly had a private healthcare facility in the neighborhood implying absence of competition whereas 12 is the highest number of private healthcare facilities that neighbored the public healthcare facility which implies some level of competition between a HCIII public facility and private healthcare facilities in the geographical sub-region of the study.

4.4.1 Multicollinearity test

The relation between prediction variables in the model is indicated by multicollinearity. Multicollinearity makes the standard errors of each coefficient rise hence changing the results of analysis. Additionally, multicollinearity makes significant variables under the study insignificant increasing the variance of the regression coefficients thus becoming unstable while interpreting them. Multicollinearity can be verified through running a pairwise correlation analysis and Variance Inflation Factor (VIF).

4.4.2 Pairwise Correlation Analysis

It is necessary to establish the association between the independent variables before using them for regression analysis. The direction and strength of association between variables is described by correlation though doesn't explain the basis of the relationship. Weak and very strong association are represented by the coefficients between 0.1 to 0.39, and 0.9 to 1.0 respectively while a moderate association lies between 0.4 to 0.69 (Schober & Schwarte, 2018).

Table 4.5: Showing the correlation coefficients between Explanatory variables for TE under Tobit model.

	TE_Score	**lnInco**	**Un_rate**	**Infect**	**Cat_Pop**	**Age<5**	**Age>65**	**HHsize**	**Loc**	**Comp**
TE_Score	1.000									
lnInc	-0.202	1.000								
	(0.285)									
Un_rate	0.156	-0.073	1.000							
	(0.411)	(0.701)								
Infect	0.201	-0.741	0.367	1.000						
	(0.287)	(0.000)	(0.046)							
Cat_Pop	0.409	0.191	0.130	-0.033	1.000					
	(0.025)	(0.313)	(0.494)	(0.862)						
Age<5	0.491	0.012	-0.025	0.134	0.762	1.000				
	(0.006)	(0.952)	(0.895)	(0.479)	(0.000)					
Age>65	0.320	-0.882	-0.035	0.710	-0.114	0.029	1.000			
	(0.085)	(0.000)	(0.854)	(0.000)	(0.550)	(0.879)				

HHsize	-0.298	0.504	0.385	-0.413	-0.005	-0.085	-0.487	1.000		
	(0.110)	(0.005)	(0.036)	(0.023)	(0.979)	(0.656)	(0.006)			
Loc	0.260	-0.164	0.149	0.319	0.195	-0.025	0.131	-0.383	1.000	
	(0.166)	(0.387)	(0.433)	(0.086)	(0.303)	(0.898)	(0.490)	(0.037)		
Comp	-0.042	0.047	-0.340	-0.255	-0.342	-0.236	-0.125	-0.114	-0.167	1.000
	(0.825)	(0.807)	(0.066)	(0.175)	(0.065)	(0.210)	(0.510)	(0.547)	(0.379)	

Source: Researcher's own computation (2023)

The results revealed that catchment population (Cat_Pop), Age<5, Age>65 had statistically significant association with TE scores. The remaining variables had no statistically significant association with technical efficiency of healthcare facilities. Furthermore, the pairwise correlation coefficients show lower cases of association among the independent variables revealing lower cases of multicollinearity thus making variables fit for regression analysis.

4.4.3 Variance Inflation Factor (VIF)

VIF is performed to establish the level of multicollinearity among the variables in the model such that when VIF = 1, there is no multicollinearity VIF between 1 to 5 shows moderate levels while VIF > 10 shows very high levels of multicollinearity (Shrestha, 2020). The VIF test results indicate no serious cases of multicollinearity among the variables under the study thus making them good for use in the analysis.

Table 4.6: Showing VIF coefficients for the Tobit regression variables

Var	**lnInc**	**Age>65**	**Infect**	**Cat_Pop**	**Age<5**	**Un_rate**	**HHsize**	**Loc**	**Comp**	**Mean VIF**
VIF	6.1	6.05	4.89	4.11	3.68	2.97	2.73	1.7	1.4	3.73

Source: Researcher's own computation (2023)

The results show a mean VIF of 3.73 which is lower than VIF recommended value of 5, hence confirming low levels of multicollinearity thus making all the variables suitable for use in the analysis. This guarantees the reliability and stability of the coefficients.

4.4.4 Tobit Regression model

Tobit regression model was applied to determine the influence of socioeconomic characteristics of the patients on the performance of the HCIII facilities. In this case, second stage estimation using TE scores generated from DEA model in stage one acted as a dependent variable while socio economic indicators namely; income levels, unemployment rate, infectious diseases, catchment population, age below 5 and above 65 years, household size, location of the facility and finally the level of competition were the applied in the regression as independent variables. Tobit model is suitable for censored values hence applicable. The TE scores are censored from zero (0) to one (1). The Tobit regression results are presented in the table below;

Table 4.7: Showing Tobit regression results for socioeconomic determinants of technical efficiency

TE Score	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
lninc	0.1184	0.1067	1.1100	0.2800	-0.1034	0.3403
Un_rate	2.1245	0.4219	5.0400	0.0000	1.2470	3.0019
Infect	-0.0001	0.0000	-4.2100	0.0000	-0.0002	-0.0001
Cat_Pop	-0.0002	0.0000	-1.9600	0.0630	0.0000	0.0000
Age<5	0.0003	0.0001	3.7500	0.0010	0.0001	0.0005
Age>65	0.0004	0.0002	2.3100	0.0310	0.0000	0.0008
HHsize	-0.1623	0.0453	-3.5900	0.0020	-0.2564	-0.0682

Loc	0.2839	0.1149	2.4700	0.0220	0.0449	0.5228
Comp	0.0456	0.0235	1.9400	0.0660	-0.0033	0.0945
_cons	-1.2599	1.4771	-0.8500	0.4030	-4.3318	1.8120
sigma	0.2292	0.0531			0.1188	0.3397
Tobit regression			No of Obs.		=	30
			F(9,21)		=	10.660
			Prob > F		=	0.000
Log pseudo likelihood		=	-5.047	Pseudo R^2	=	0.781
Obs.	summary:	0	left-censored observations			
		16	uncensored observations			
			right-censored observations			
		14	at TE Score>=1			

Source: Researcher's own computation (2023)

Interpretation of the results

The regression coefficient for unemployment rate variable (Un_rate), shows a positive relationship such that a unit increase in the rate of unemployment results into an increase in the level of technical efficiency by 2.1 percent for a facility. A priori expectation holds for a mixed effect for the two variables. This relationship is statistically significant (p=0.000).

The coefficient for infectious diseases (Infect) variable indicates that a unit increase in the infectious diseases patient population results into a decrease in the level of technical efficiency by 0.01 percent. However, a positive relationship is held by economic theory between the two variables. This relationship is statistically significant (p=0.000).

The coefficient for catchment population (Cat_Pop), reveals a negative relationship between catchment population and technical efficiency for a public health facility. Specifically, an increase in the population by a person reduces technical efficiency of the facility by 0.02 percent. Economic theory holds for a mixed relationship between the two variables. This relationship is statistically significant (p=0.063).

For the population aged below five years (Age<5), the findings show that unit increase in the population of the age bracket served by a facility results into increase in the technical efficiency by 0.03 percent and this relationship matches with the expected a priori. The relationship between the two variables is statistically significant (p=0.001).

The regression coefficient for the population above 65 five years (Age> 65) portrays a positive relationship between the two variables. Specifically, a unit increase in the population above sixty-five years (>65) served by a facility results into increase in the technical efficiency by 0.04percent. The findings however contradict with the expected a priori. The relationship is statistically significant (p=0.031).

For household size variable (HHsize), the coefficient indicates a negative relationship between the two variables, such that an increase in the size of household members by a person reduces technical efficiency of a facility by 16 percent. This relationship is statistically significant (p=0.002). The findings however contradict with the economic theory which holds for a positive relationship between the two variables.

The regression coefficient for location (Loc) reveals a positive relationship between urban location and technical efficiency of a facility. Specifically, a facility located in an urban area has 28 percent chances higher than a facility located in rural area of operating technically efficient.

The expected a priori is mixed both positive and negative according to literature for the two variables. The relationship is statistically significant (p=0.022).

Finally, there is a positive relationship between competition (Comp) and technical efficiency according to the regression coefficient. Specifically, an extra private facility established in the catchment area served by the public HCIII facility, results into an increase in the level of technical efficiency by 5 percent. Economic theory holds for a mixed relationship between two variables such that it can increase and decrease technical efficiency for a facility. The relationship is statistically significant (p=0.066).

The pseudo R^2 shows that the sampled data was generally good. The standard errors and p-values are significant rather than goodness of fit of the general model in Tobit regression analysis. The model is censored to the right. The necessary post estimation tests like serial correlation, heterogeneity were taken guard against by running a robust Tobit regression. Robust regression checks for outliers and impact of extreme observations. Robustness, produces efficient and reliable results (Huang et al., 2016).

4.4.5 Discussion of Tobit regression results

The coefficient reveals a positive relationship between unemployment rate and technical efficiency of a facility implying that increase in the level of unemployed patients served by a facility increases the technical efficiency. The intuition is that more unemployed population in the catchment area served by a facility leaves them with no alternative other than resorting to the public facility for healthcare services due to inability to afford services from private facilities, given limited or no incomes to meet the user for fees payments required by private facilities. This results into maximum utilization of health resources available to the public facilities. However, this may pause potential disastrous effects once unemployment rate reaches extreme levels due to the fact that it may result into over utilization of fixed facility health resources reducing technical efficiency. Contrary, In Italy a negative relationship between the two variables was established in a survey as the unemployed women between 15 and 64 years reduced the demand for formal residential medical assistance lowering significantly technical efficiency during Covid-19 pandemic (Cepparulo & Giuriato, 2022). Additionally, in a systematic review of technical efficiency of healthy systems, a negative association was establishes between high rates of unemployment and technical efficiency of global health systems (Mbau et al., 2023).

The negative relationship between catchment population and technical efficiency of healthcare facilities implies that an increase in population in the catchment area served by a facility lowers its technical efficiency. The intuition is that healthcare resources are over stressed to meet the multiple demands from many people reducing the technical efficiency. Similar results of a negative relationship between the two variables was established in Iran, (Yousefi Nayer et al., 2022) and Europe, (Lupu & Tiganasu, 2022). In Kenya, the same relationship was established due to the fact that higher population densities in the catchment were not matched with healthcare resources thus compromising health outcomes (Mbau et al., 2023). Additionally, a negative significant relationship was showed between higher population densities and women while accessing healthcare services in Sub Saharan Africa, citing that it results into excess population over the available resources lowering the technical efficiency for the serving facility, thus larger population is associated with complex healthcare needs exerting more pressure on fixed hospital resources and compromised quality of care (Dominic et al., 2020). Contrary, a positive relationship between population density and technical efficiency was established in Kenya (Barasa et al., 2021), Jordan (Alatawi et al., 2020b) and in Germany (Vrabková & Lee,

2023) with reasons that higher population density reduces percapita cost of healthcare provision with many people while small population density results into resource wastage. Furthermore, a positive relationship was confirmed in Chile for areas with a high population density in the catchment of a healthcare facility due to the fact that it reduces the distances to populations and makes it easier for healthcare systems to organize and utilize their services infrastructure as well as per capita cost of healthcare (Mbau et al., 2023).

An increase in infectious diseases patients served by a facility reduces its technical efficiency. The intuition is derived from the fact that the infectious diseases spread very fast once contracted and needs immediate intervention to control the spread. In some cases, the number of acute patients reporting for healthcare services may exceed what the capacity of facility can afford at a time resulting into putting more stress on the available resources like hospital beds and medical staff. This lowers technical efficiency as the facility cannot be able to produce the corresponding healthcare services required by many infected patients. This is very common in cases of diseases outbreaks that are spread from one person to another leading to congestion of hospital beds and numbers of patients exceeding the available medical staff. The findings however, contradict with findings established in a survey on public hospitals in Saudi Arabia where public hospitals that served more patients with infectious diseases were associated with higher TE scores unlike those serving patients with chronic diseases (Alatawi et al., 2020a). The fronted reason is that infectious diseases patients often require acute treatment and for a short time period for outpatient services followed by antibiotic sessions for each patient unlike for chronic disease patients who require treatment for a prolonged time span demanding for more health resources for each patient.

The study findings indicate a positive relationship between the patients below the age of 5 (children) and TE implying that a facility that serves more patient children (below 5 years) is associated with higher levels of a technical efficiency. The study findings show higher levels of immunizations recorded by facilities in the study area which is one of the services received by the children in the early years. This can partially explain high utilization levels of health resources and technical efficiency especially for those facilities that administered more immunizations. Similar findings were established in Norway, with a reason that children under 5 years may be exposed to a higher level of morbidity, therefore higher need for healthcare services especially in their early childhood stage resulting into more health resource utilization in the hospitals (Klitkou et al., 2017).

The study findings reveal a negative relationship between patients above 65 years and TE scores of a facility. This implies that a facility that serves more patient population above the age of 65 uses more resources to meet the healthcare demands for the elderly sick population. This is backed by the fact that health depreciates with age implying more age associated diseases especially with the elderly population which calls for more resources to maintain life. Similar findings were established by studies done mainly in European countries, where majority of the elderly people (>65) portrayed a negative relationship during covid-19 pandemic and technical performance of health facilities. Additionally, elderly persons are associated with more health complications and higher probability of death especially during a health crisis due to vulnerability. Countries like Italy, Germany witnessed more deaths cases among the elderly population. Additionally, it calls for more resources to meet and maintain the health demands for such population since majority tend to associate with age specific diseases (Lupu & Tiganasu, 2022). In Italy, a negative and insignificant relationship was evidenced in a survey during Covid-

19 pandemic with a reason that the elderly population is always disconnected from the distribution of public expenditure and distribution of the real and social needs (Cepparulo & Giuriato, 2022).

The study findings indicate that an increase in the household members result into declining levels of technical efficiency for a facility. The intuition is that more family members result into excessive number of people seeking for healthcare services which exerts more pressure on fixed resources for a facility hence reducing its technical efficiency as it results into compromised quality of the health output provided. However, the findings in Saudi Arabia where family size showed no significant effect on technical efficiency of hospitals (Alsubaie et al., 2016).

The study findings show that a health facility established in an urban area is 28 percent more chanced than one in rural location to operate technically efficient. This is explained by the fact that towns are always busy due to population concentration which imply more demand for healthcare services from a facility calling for more health resource utilization by a facility. The study findings are consistent with the survey results in Turkey which established a positive relationship between the two variables (Bağci & Konca, 2021; İlgün & Konca, 2019). On the other hand, a facility located in a rural area is associated with low level of utilization of healthcare resources such as medical staff and hospital beds which reduces the facility technical efficiency (Yildiz et al., 2018). Similar results for a lower technical efficiency for rural public hospitals in Cameroon were established in a study by Christopher with an explanation that most people in rural areas prefer to use traditional methods of treating themselves limiting usage of available health resources (Christopher, 2016). A recent systematic review of technical efficiency literature indicates low levels of technical efficiency in rural areas due to the fact that there are low levels of employment opportunities and low incomes that affect the healthcare utilization (Mbau et al., 2023). However, urban location was found to reduce technical efficiency in Pennsylvania, though insignificant (Kim et al., 2021).

There is generally a belief that competition plays a big role in influencing technical efficiency. The Tobit coefficient reveals that an increase in the level of competition between private and public healthcare facilities increases the technical efficiency of a facility. The intuition is that competition conditions healthcare producers to provide more appealing quality of healthcare services to the patients. However, there is a mixed literature of the relationship between the two variables with some literature reporting a positive, otherwise for other studies (Goddard, 2015). Competition among public hospitals in Togo was found to increase technical efficiency due to the fact that there is improvement in care quality (satisfaction) (Atake, 2019). However, high competition was found to decrease technical efficiency in Pennsylvania hospitals reasoning that it forces hospitals to invest more into hospital inputs compared to those in less competitive markets (Kim et al., 2021). In Turkey, hospitals with more competition were also associated with lower efficiency as high competition forced hospitals to incur higher costs than those in less competitive markets in order to have high quality expensive medical care amenities, equipment and consequently translating into higher fee-for-services charged (Özgen Narcı et al., 2015).

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS OF THE STUDY

5.0 Introduction

This chapter presents the summary and conclusions of the study findings as well as putting forward the possible recommendations to improve technical efficiency in public HCIII facilities in the South Western Uganda. Areas of further study are also suggested in this chapter.

5.1 Summary of the results

DEA results indicate that 47 percent of the sampled facilities were technically efficient with an average TE score of 72 percent.

The slack values show evidence of resource underutilization mainly hospital beds and EMHS while output slack values reveal the need to augment health output among inefficient healthcare facilities mainly laboratory tests, health education sessions and immunizations to increase technical efficiency.

The Tobit regression results mainly for socio economic factors that significantly affect the TE for the public healthcare facilities indicate that;

A high rate of unemployment was found to condition people to majorly rely on public health facilities for healthcare services which makes the facilities to utilize more healthcare resources.

More infectious diseases' patients put more stress on fixed health facility resources reducing technical efficiency. Several infectious diseases recorded in the area include; Urinary Tract Infections (UTIs), Sexually Transmitted Diseases (STDs), sleeping sickness, genital ulcers, infections due to Sexual Gender Based Violence (SGBV), other emerging infections like influenza.

High population density in the catchment area of the facility reduces technical efficiency for a facility due to resource constraints to match the high population healthcare services demanded.

The increase in patient population with age below 5 and above 65 years calls for more resource utilization by a facility to meet the health demands by the children and elderly thus increasing the technical efficiency of a facility.

Increase in household members implies more people seeking for health care attention which turns out to be resource burdening to the facility reducing its technical efficiency.

Health facilities in urban locations are associated with modern hospital infrastructure, easy accessibility of services and reliable presence of medical staff at the facility increasing technical efficiency unlike in rural areas where the incentives are limited with poor accessibility to the healthcare facilities which reduces the technical efficiency of rural based healthcare facilities.

Competition between public and private healthcare facilities increases technical efficiency. This is because of commitment to ensure and deliver quality healthcare services by the facilities.

5.2 Study conclusions

The study mainly analyses the TE of public HCIII facilities in South western Uganda using DEA technique and secondary data for the financial year 2020/21 from UBOS, DHIS and DPUs. The results reveal that on average the HCIII facilities were 72 percent technically efficient.

Economic savings can be achieved by reallocating the EMHS funds and beds to avail funds for increasing on health education sessions and conducting more immunizations and laboratory tests.

The Tobit regression results show that unemployment rate, infectious diseases, age below 5 and above 65, household size, location, catchment population and competition are significant in determining technical efficiency among public health facilities.

High population density, more Infectious diseases patients and increase in household members reduce technical efficiency. The remaining significant variables significantly increase technical efficiency of public health facilities.

Easy accessibility to urban healthcare facilities increases on technical efficiency. This is attributed to improved social services in towns that attract more people. Contrary in rural areas, poor services are associated with low levels of   while healthcare facilities in rural areas low levels of technical efficiency due to poor accessibility to facilities. Additionally, the availability of traditional medication forms alternatives to medication from healthcare facilities which reduces technical efficiency in rural healthcare facilities.

5.3 Policy recommendations

Faced with resource constraints amidst ever growing population healthcare demands, there is a need to ensure efficient allocation and utilization of resources in the health sector by the ministry of health of Uganda and other stakeholders to achieve efficiency. The following policy implications are drawn from the study findings for policy guidance towards achieving technical efficiency;

Reallocate resources within facilities not only to reduce resource underutilization but also to augment health outputs.

Provision of additional resources to facilities serving more population in their catchments to match the high healthcare demands. This can be both human resources and medical supplies. The same policy can also be applied to facilities serving unemployed patient populations to ensure optimum health output production.

Control the rapid spread of infectious diseases by encouraging proper sanitation and hygiene practices among the communities to reduce the pressure on hospital beds and medical staff.

Allocate resources based on the catchment population in the area. This can be done by relying on updated population database to allocate sufficient resources to the available population.

Improvement of the social infrastructure like roads, electricity, safe water so as to enable easy accessibility to social services especially in rural areas. This can increase on accessibility to facilities in rural areas thus enabling the facilities to improve on technical efficiency.

5.4 Areas for further research

Due to the scope and other constraints of the study; some areas were left unleashed by this mentioned for further study to establish their effect on performance of the health system. They include;

(i) Socioeconomic determinants of technical efficiency among public healthcare facilities using SFA approach.

(ii) Effect of distance travelled by a patient to a facility on the technical efficiency of health facilities in Uganda.

(iii) Effect of gender on technical efficiency of public healthcare facilities in Uganda.

5.5 Study limitations

The DEA model applies a simplistic assumption of similar attributes (qualities) across the DMUs but in real sense, a lot in diverse is commonly realized among the healthcare facilities in terms of quality of healthcare output.

The sample size appears small given the population of the HCIII facilities in the area of study (30 of 53). However, this was taken care of by guidance of sample selection under DEA principle of the sample size being 3 times greater than the summation of inputs and outputs.

The study was restricted to public ownership for the facilities excluding the private facilities for a comparative purpose among the two categories by ownership.

Despite the above-mentioned limitations, the study findings remain relevant for policy and decision making in order to achieve technical efficiency in the health sector.

References

Agarwal, S. (2011). *IJOR new slack model*.

Ahimbisibwe, E. (2019). *Efficiency in Utilization of the Resources Allocated to Lower Level Health Facilities in Uganda*. 1–27.

Ahmed, S., Hasan, M. Z., Laokri, S., Jannat, Z., Ahmed, M. W., Dorin, F., Vargas, V., Khan, J. A. M., Chai, P., Zhang, Y., Zhou, M., Liu, S., Kinfu, Y., Li, Y., Zhao, Y., Xixin Niu, Zhou, W., Tian, J., Davies, N. E., … Martín-Martín, J. J. (2020). Measuring the Efficiency of Public Hospitals in Kuwait: A Two-Stage Data Envelopment Analysis and a Qualitative Survey Study. *Cost Effectiveness and Resource Allocation*, *12*(1), 1–9. https://doi.org/10.5539/gjhs.v12n3p121

Ajanga, M. (2021). *Allocative Inefficiency of General Hospitals in Poor Countries: A Case Study of Uganda*. *3*(1), 1–11. https://doi.org/10.37284/eajis.3.1.346.128

Alatawi, A. D., Niessen, L. W., & Khan, J. A. M. (2020a). Determinants of Technical Efficiency in Public Hospitals: The Case of Saudi Arabia. *Health Economics Review*, *10*(1), 1–11. https://doi.org/10.1186/s13561-020-00282-z

Alatawi, A. D., Niessen, L. W., & Khan, J. A. M. (2020b). Efficiency evaluation of public hospitals in Saudi Arabia: An application of data envelopment analysis. *BMJ Open*, *10*(1), 1–10. https://doi.org/10.1136/bmjopen-2019-031924

Alchian, A., & Demsetz, H. (1972). Linked references are available on JSTOR for this article : Production , Information Costs , and Economic Organization. *The American Economic Review*, *62*(5), 777–795. https://knowledgehub.unsse.org/es/knowledge-hub/relacionesentre-los-ods-el-plan-para-una-decada-cooperativa-y-el-balance-social-en-cooperativas-2/

Ali, M., Debela, M., & Bamud, T. (2017). Technical efficiency of selected hospitals in Eastern Ethiopia. *Health Economics Review*, *7*(1). https://doi.org/10.1186/s13561-017-0161-7

Alsabah, A. M., Haghparast-Bidgoli, H., & Skordis, J. (2020). Measuring the Efficiency of Public Hospitals in Kuwait: A Two-Stage Data Envelopment Analysis and a Qualitative Survey Study. *Global Journal of Health Science*, *12*(3), 121. https://doi.org/10.5539/gjhs.v12n3p121

Alsubaie, A. M., Almohaimede, K. A., Aljadoa, A. F., Jarallah, O. J., Althnayan, Y. I., & Alturki, Y. A. (2016). Socioeconomic factors affecting patients' utilization of primary care services at a Tertiary Teaching Hospital in Riyadh, Saudi Arabia. *Journal of Family and Community Medicine*, *23*(1), 6–11. https://doi.org/10.4103/2230-8229.172223

Arhin, K., Opoku, A., Boso, R., & Acheampong, K. (2023). Healthcare Analytics A double bootstrap data envelopment analysis model for evaluating malaria spending efficiency in Sub-Saharan Africa. *Healthcare Analytics*, *3*(May 2022), 100137. https://doi.org/10.1016/j.health.2023.100137

Asbu, E. Z., Masri, M. D., & Naboulsi, M. Al. (2020). Determinants of Hospital Efficiency: insights from the literature. *International Journal of Healthcare*, *6*(2), 44-53. https://doi.org/10.21203/rs.2.15354/v2

Atake, E. (2019). *Analysis of the Technical Efficiency of Public Hospitals in Togo : A non-Parametric Approach* (Issue January).

Auster, R., Leveson, I., & Sarachek, D. (1969). The Production of Health, an Exploratory Study.

The Journal of Human Resources, *4*(4), 411. https://doi.org/10.2307/145166

Ayiko, R., Mujasi, P. N., Abaliwano, J., Turyareeba, D., Enyaku, R., Anguyo, R., Odoch, W., Bakibinga, P., & Aliti, T. (2020). Levels, trends and determinants of technical efficiency of general hospitals in Uganda: Data envelopment analysis and Tobit regression analysis. *BMC Health Services Research*, *20*(1), 1–12. https://doi.org/10.1186/s12913-020-05746-w

Babalola, T. K., & Moodley, I. (2020). Assessing the Efficiency of Health-care Facilities in Sub-Saharan Africa: A Systematic Review. *Health Services Research and Managerial Epidemiology*, *7*, 233339282091960. https://doi.org/10.1177/2333392820919604

Bağci, H., & Konca, M. (2021). Evaluating the Technical Efficiency of Hospitals Providing Tertiary Health Care in Turkey: An Application Based on Data Envelopment Analysis. *Hospital Topics*, *99*(2), 49–63. https://doi.org/10.1080/00185868.2020.1830008

Banker, R. D., Bardhan, I., & Cooper, W. W. (1996). A note on returns to scale in DEA. *European Journal of Operational Research*, *88*(3), 583–585. https://doi.org/10.1016/0377-2217(94)00281-9

Barasa, E., Musiega, A., Hanson, K., Nyawira, L., Mulwa, A., Molyneux, S., Maina, I., Tsofa, B., Normand, C., & Jemutai, J. (2021). Level and determinants of county health system technical efficiency in Kenya: two stage data envelopment analysis. *Cost Effectiveness and Resource Allocation*, *19*(1), 1–11. https://doi.org/10.1186/s12962-021-00332-1

Bruning, E. R., & Register, C. A. (1989). Technical efficiency within hospitals: Do profit incentives matter? *Applied Economics*, *21*(9), 1217–1233. https://doi.org/10.1080/758520662

Cavalcanti1, I. T. (2022). *Efficiency in hospital care in Brazilian capitals for the period 2014-2017*. *14*(64), 52–64. https://doi.org/10.21115/JBES.v14.n1.(Suppl.1)

Cepparulo, A., & Giuriato, L. (2022). The residential healthcare for the elderly in Italy: some considerations for post-COVID-19 policies. *European Journal of Health Economics*, *23*(4), 671–685. https://doi.org/10.1007/s10198-021-01388-9

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, Z., Chen, X., Gan, X., Bai, K., Baležentis, T., & Cui, L. (2020). Technical efficiency of regional public hospitals in china based on the three-stage dea. *International Journal of Environmental Research and Public Health*, *17*(24), 1–17. https://doi.org/10.3390/ijerph17249383

Chiu, C. M., Chen, M. S., Lin, C. S., Lin, W. Y., & Lang, H. C. (2022). Evaluating the comparative efficiency of medical centers in Taiwan: a dynamic data envelopment analysis application. *BMC Health Services Research*, *22*(1), 1–11. https://doi.org/10.1186/s12913-022-07869-8

Christopher, P. M. (2106). Assessing the Technical Efficiency of Public Hospitals in Cameroon: An Application of Data Envelopment Analysis (DEA). *International Journal of Humanities, Social Sciences and Education*, *3*(3), 32–40. https://doi.org/10.20431/2349-0381.0303005

Clement, J. P., Valdmanis, V. G., Bazzoli, G. J., Zhao, M., & Chukmaitov, A. (2008). Is more better? An analysis of hospital outcomes and efficiency with a DEA model of output congestion. *Health Care Management Science*, *11*(1), 67–77.

https://doi.org/10.1007/s10729-007-9025-8

Davis, H. S. (2018). the Measurement of Productive Efficiency. *The Industrial Study of Economic Progress*, *120*(3), 16–35. https://doi.org/10.2307/j.ctv5rdxd5.7

Dominic, A., Ogundipe, A., & Ogundipe, O. (2020). Determinants of Women Access to Healthcare Services in Sub-Saharan Africa. *The Open Public Health Journal*, *12*(1), 504–514. https://doi.org/10.2174/1874944501912010504

Emanuel, E. J., Gudbranson, E., Van Parys, J., Grtz, M., Helgeland, J., & Skinner, J. (2021). Comparing Health Outcomes of Privileged US Citizens with Those of Average Residents of Other Developed Countries. *JAMA Internal Medicine*, *181*(3), 339–344. https://doi.org/10.1001/jamainternmed.2020.7484

Emrouznejad, A., & Makoudode, P. (2007). *18% 31%*.

Fumbwe, F., Lihawa, R., Andrew, F., Kinyanjui, G., & Mkuna, E. (2021). Examination on level of scale efficiency in public hospitals in Tanzania. *Cost Effectiveness and Resource Allocation*, *19*(1), 1–10. https://doi.org/10.1186/s12962-021-00305-4

Gaynor, M., & Town, R. J. (2011). Competition in Health Care Markets. In *Handbook of Health Economics* (Vol. 2). Elsevier B.V. https://doi.org/10.1016/B978-0-444-53592-4.00009-8

Goddard, M. (2015). Competition in healthcare: Good, bad or ugly? *International Journal of Health Policy and Management*, *4*(9), 567–569. https://doi.org/10.15171/ijhpm.2015.144

Grigoli, F., & Kapsoli, J. (2018). Waste not, want not: The efficiency of health expenditure in emerging and developing economies. *Review of Development Economics*, *22*(1), 384–403. https://doi.org/10.1111/rode.12346

Grossman, M. (1971). Demand for Health - Theoretical and Empirical Investigation. *Econometrica*, *39*(4), 77-.

Hadji, B., & Degoulet, P. (2023). *Measuring hospital technical efficiency with data envelopment analysis , application to 20 Paris public university hospitals*. 1–20.

Han, A., & Lee, K. H. (2021). The impact of public reporting schemes and market competition on hospital efficiency. *Healthcare (Switzerland)*, *9*(8), 1–13. https://doi.org/10.3390/healthcare9081031

Huang, D., Cabral, R., & Torre, F. Dela. (2016). Robust Regression. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *38*(2), 363–375. https://doi.org/10.1109/TPAMI.2015.2448091

Hussain, Z., Miao, C., Zhao, Z., & Wang, Y. (2022). Nexus Between Economic Efficiency, Healthcare, and Environmental Expenditures: A Perspective of BRI Countries. *Frontiers in Public Health*, *10*(February), 1–18. https://doi.org/10.3389/fpubh.2022.842070

İlgün, G., & Konca, M. (2019). Assessment of efficiency levels of training and research hospitals in Turkey and the factors affecting their efficiencies. *Health Policy and Technology*, *8*(4), 343–348. https://doi.org/10.1016/j.hlpt.2019.08.008

Kim, Y., Lee, K. H., & Choi, S. W. (2021). Multifaced evidence of hospital performance in Pennsylvania. *Healthcare (Switzerland)*, *9*(6), 1–11. https://doi.org/10.3390/healthcare9060670

Klitkou, S. T., Iversen, T., Stensvold, H. J., & Rønnestad, A. (2017). Use of hospital-based health care services among children aged 1 through 9 years who were born very preterm - A population-based study. *BMC Health Services Research*, *17*(1), 1–13. https://doi.org/10.1186/s12913-017-2498-3

Kohler, J. C., & Bowra, A. (2020). Exploring anti-corruption, transparency, and accountability in the World Health Organization, the United Nations Development Programme, the World Bank Group, and the Global Fund to Fight AIDS, Tuberculosis and Malaria. *Globalization and Health*, *16*(1), 1–10. https://doi.org/10.1186/s12992-020-00629-5

Küçük, A., Özsoy, V. S., & Balkan, D. (2020). Assessment of technical efficiency of public hospitals in Turkey. *European Journal of Public Health*, *30*(2), 230–235. https://doi.org/10.1093/eurpub/ckz143

Kunz, A. H., & Pfaff, D. (2002). *Agency theory , performance evaluation , and the hypothetical construct of intrinsic motivation*. *27*, 275–295.

Li, Z., Zhang, W., Kong, A., Ding, Z., Wei, H., & Guo, Y. (2021). Configuration analysis of influencing factors of technical efficiency based on DEA and FSQCA: Evidence from China's medical and health institutions. *Risk Management and Healthcare Policy*, *14*, 49–65. https://doi.org/10.2147/RMHP.S282178

Liu, J., He, B., Xu, X., Zhou, L., Li, J., Wang, G., & Chen, Y. (2019). Determinants of efficiency growth of county-level public hospitals-evidence from Chongqing, China. *BMC Health Services Research*, *19*(1), 1–15. https://doi.org/10.1186/s12913-019-4609-9

Lupu, D., & Tiganasu, R. (2022). COVID-19 and the efficiency of health systems in Europe. *Health Economics Review*, *12*(1), 1–15. https://doi.org/10.1186/s13561-022-00358-y

Magee, R. P. (2001). Discussion of "Contracting theory and accounting." *Journal of Accounting* *and Economics*, *32*(1–3), 89–96. https://doi.org/10.1016/S0165-4101(01)00020-9

Mahate, A., Hamidi, S., & Akinci, F. (2016). Measuring the Effect of Size on Technical Efficiency of the United Arab Emirates Hospitals. *Global Journal of Health Science*, *9*(3), 116. https://doi.org/10.5539/gjhs.v9n3p116

Marschall, P., & Flessa, S. (2009). Assessing the efficiency of rural health centres in Burkina Faso: An application of Data Envelopment Analysis. *Journal of Public Health*, *17*(2), 87–95. https://doi.org/10.1007/s10389-008-0225-6

Mbau, R., Musiega, A., Nyawira, L., Tsofa, B., Mulwa, A., Molyneux, S., Maina, I., Jemutai, J., Normand, C., Hanson, K., & Barasa, E. (2023). Analysing the Efficiency of Health Systems: A Systematic Review of the Literature. *Applied Health Economics and Health Policy*, *21*(2), 205–224. https://doi.org/10.1007/s40258-022-00785-2

Medarević, A., & Vuković, D. (2021). Efficiency and productivity of public hospitals in Serbia using dea-malmquist model and tobit regression model, 2015–2019. *International Journal of Environmental Research and Public Health*, *18*(23). https://doi.org/10.3390/ijerph182312475

Ministry of Health. (2018). Uganda Essential Medicines and Health Supplies Management Manual. *Report*, *November*. http://library.health.go.ug/publications/medicines/uganda-essential-medicines-and-health-supplies-management-manual-2018

MOH. (2019). National Health Facility Master List 2018. *Ministry of Health Uganda*, *November*, 1–164. http://library.health.go.ug/sites/default/files/resources/National Health Facility Master List 2018_0.pdf

Mohamadi, E., Kiani, M. M., & Olyaeemanesh, A. (2022). *Two-Step Estimation of the Impact of Contextual Variables on Technical Efficiency of Hospitals : The Case Study of Public Hospitals in Iran*. *9*(January), 1–8. https://doi.org/10.3389/fpubh.2021.785489

Mujasi, P. N., Asbu, E. Z., & Puig-Junoy, J. (2016). How efficient are referral hospitals in Uganda? A data envelopment analysis and tobit regression approach. *BMC Health Services Research*, *16*(1), 1–14. https://doi.org/10.1186/s12913-016-1472-9

Ngobeni, V., Breitenbach, M. C., & Aye, G. C. (2020). Technical efficiency of provincial public healthcare in South Africa. *Cost Effectiveness and Resource Allocation*, *18*(1), 1–19. https://doi.org/10.1186/s12962-020-0199-y

NPA. (2020). The Third National Development Plan (NDP III) 2020/21-2024/25. *Republic of Uganda*, *1*(January), 1–310. http://envalert.org/wp-content/uploads/2020/06/NDP-3-Finale.pdf

Ojwang OYIEKE, S., E. OSORO, N., & Innocent KARAMAGI, J. (2021). Determinants of Technical Efficiency of Hospitals in Kenya: 2012-2016. *International Journal of Business, Economics and Management*, *8*(1), 19–30. https://doi.org/10.18488/journal.62.2021.81.19.30

Özgen Narcı, H., Ozcan, Y. A., Şahin, İ., Tarcan, M., & Narcı, M. (2015). An examination of competition and efficiency for hospital industry in Turkey. *Health Care Management Science*, *18*(4), 407–418. https://doi.org/10.1007/s10729-014-9315-x

Pauly, M., Redisch, M., The, S., Economic, A., Mar, N., Pauly, B. M., & Redisch, M. (1973). The Not-For-Profit Hospital as a Physicians ' Cooperative. *American Economic Association*, *63*(1), 87–99.

Pproach, D. A. T. A. A., Chen, W., & Lin, Y. (2015). *Stimating a*. *4*, 154–169.

Şahin, B., & İlgün, G. (2019). Letter to editor: about criticisms regarding manuscript entitled "assessment of the impact of public hospital associations (PHAs) on the efficiency of hospitals under the Ministry of Health in Turkey with data envelopment analysis." *Health Care Management Science*, *22*(3), 448–450. https://doi.org/10.1007/s10729-019-09475-3

Schober, P., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia and Analgesia*, *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Shrestha, N. (2020). Detecting Multicollinearity in Regression Analysis. *American Journal of Applied Mathematics and Statistics*, *8*(2), 39–42. https://doi.org/10.12691/ajams-8-2-1

Smith, P. C., & Street, A. (2005). Measuring the efficiency of public services: The limits of analysis. *Journal of the Royal Statistical Society. Series A: Statistics in Society*, *168*(2), 401–417. https://doi.org/10.1111/j.1467-985X.2005.00355.x

Stefko, R., Gavurova, B., & Kocisova, K. (2018). Healthcare efficiency assessment using DEA analysis in the Slovak Republic. *Health Economics Review*, *8*(1). https://doi.org/10.1186/s13561-018-0191-9

Tindimwebwa, K. (2018). Efficiency Estimates of Public Health Center II Facilities in Southwestern Uganda. *SocArXiv*, *33*(3), 19–26. https://doi.org/10.3969/j.issn.1009-4393.2017.34.029

Top, M., Konca, M., & Sapaz, B. (2020). Technical efficiency of healthcare systems in African countries: An application based on data envelopment analysis. *Health Policy and*

Technology, *9*(1), 62–68. https://doi.org/10.1016/j.hlpt.2019.11.010

UBOS. (2020). Uganda National Survey Report 2019/2020. *UNHS*.

Valdmanis, V. G., Rosko, M. D., & Mutter, R. L. (2008). Hospital quality, efficiency, and input slack differentials. *Health Services Research*, *43*(5 P2), 1830–1848. https://doi.org/10.1111/j.1475-6773.2008.00893.x

Van Malderen, C., Amouzou, A., Barros, A. J. D., Masquelier, B., Van Oyen, H., & Speybroeck, N. (2019). Socioeconomic factors contributing to under-five mortality in sub-Saharan Africa: A decomposition analysis. *BMC Public Health*, *19*(1), 1–19. https://doi.org/10.1186/s12889-019-7111-8

Vrabková, I., & Lee, S. (2023). Approximating the influence of external factors on the technical efficiency score of hospital care: evidence from the federal states of Germany. *Health Economics Review*, *13*(1), 1–14. https://doi.org/10.1186/s13561-022-00414-7

Wu, X., Zhu, X., Wu, G., & Ding, W. (2013). *Ăłă Dŝŷŝŷő ǁŝłś Ŝő Ăłă*. *Ibm 2012*.

Xu, K., Soucat, A., Kutzin, J., Brindley, C., Maele, N. Vande, Touré, H., Garcia, M. A., Li, D., Barroy, H., Flores, G., Roubal, T., Indikadahena, C., Cherilova, V., & Siroka, A. (2018). Public Spending on Health: A Closer Look at Global Trends:Geneva: World Health Organization. In *Reporte Global OMS*. http://apps.who.int/bookorders.

Yildiz, M. S., Heboyan, V., & Khan, M. M. (2018). Estimating technical efficiency of Turkish hospitals: Implications for hospital reform initiatives. *BMC Health Services Research*, *18*(1), 1–16. https://doi.org/10.1186/s12913-018-3239-y

Yousefi Nayer, M., Fazaeli, A. A., & Hamidi, Y. (2022). Hospital efficiency measurement in the west of Iran: data envelopment analysis and econometric approach. *Cost Effectiveness and Resource Allocation*, *20*(1), 1–6. https://doi.org/10.1186/s12962-022-00341-8

APPENDIX: DMU NAMES

S/N	DMU	FACILITY NAME
1	DMU1	Kaharo HC III
2	DMU2	Ruhinda HC III
3	DMU4	Bwama HC III
4	DMU7	Kagezi HC III
5	DMU10	Bikurungu HC III
6	DMU15	Bukinda HC III
7	DMU17	Nyabihuniko HC III
8	DMU18	Muramba HC III
9	DMU20	Bufundi HC III
10	DMU21	Nyarusiza HC III
11	DMU22	Kayonza HC III
12	DMU23	Kanyantorogo HC III
13	DMU25	Bukimbiri HC III
14	DMU26	Gateriteri HC III
15	DMU27	Rugyeyo HC III
16	DMU28	Rutenga HC III
17	DMU29	Mpungu HC III
18	DMU33	Buhozi HC III
19	DMU34	Kinaaba HC III
20	DMU37	Karuhembe HC III
21	DMU38	Kisiizi HC III

22	DMU39	Nyakagyeme HC III
23	DMU40	Bwindi HC III
24	DMU41	Ruhija HC III
25	DMU42	Rusheshe HC III
26	DMU43	Rwerere HC III
27	DMU44	Kyogo HC III
28	DMU45	Bubare HC III
29	DMU51	Ikumba HC III
30	DMU53	Mpungu HC III