Discussion Paper Series

The KENYA INSTITUTE for PUBLIC POLICY RESEARCH and ANALYSIS

# Analyzing Technical Efficiency of Adult and Continuing Education Centres in Arid and Semi-Arid Lands of Kenya

Powel Murunga and Anna Muema

DP/311/2023

THE KENYA INSTITUTE FOR PUBLIC POLICY RESEARCH AND ANALYSIS (KIPPRA)

YOUNG PROFESSIONALS (YPs) TRAINING PROGRAMME

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*Kenya Institute for Public Policy Research and Analysis*

*KIPPRA Discussion Paper No. 311*
*2023*

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Published 2023

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ISBN 978 9914 738 36 0

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# Abstract

*The study assesses the technical efficiency levels within Kenya's Adult and Continuing Education Centres (ACEs) and explores the determinants influencing their efficiencies. Utilizing data from the Directorate of Adult and Continuing Education (DACE) and based on Theory of Production, this analysis employed Data Envelopment Analysis (DEA) methodology with 4 inputs and 2 outputs and considered 47 decision making units (counties) in the calculation of efficiency scores. The analysis established an average technical efficiency of 78.8 percent, 93.1 percent and 91.2 percent at national level, ASAL and Non-ASALs region respectively, indicating ASAL regions being more efficient than non-Asal regions in resource utilization. These findings indicate that the existing provision of educational services through ACEs could be increased by up to 21.2 percent, 6.9 percent, and 8.8 percent at national level, ASAL regions and non-ASAL regions respectively. To assess the factors that influence the efficiency scores, Tobit regression results indicated that factors such as internet connectivity, digital literacy programs, location (urban/rural), enrolment rates and electricity connection significantly influenced efficiency of ACE centres in ASAL regions. Policies aimed at enhancing educational provision through ACEs delivery systems may emphasize improving factors that enhance efficiency, such as a prioritizing cheaper internet access and electricity connectivity in ASAL counties, facilitating online education for out-of-school youth and adults especially for ASAL regions as this will improve performance scores of graduates ultimately improving efficiency of resources allocated to the DACE without incurring extra cost. Policies may also encourage the consolidation of smaller schools within the same locality, where feasible, to achieve economies of scale.*

## Abbreviations and Acronyms

| | |
|---|---|
| ABE | Adult and Basic Education |
| ACE | Adult and Continuing Education |
| ASAL | Arid and Semi-Arid Lands |
| APBET | Alternative Provision of Basic Education and Training |
| CBOs | Community-Based Organizations |
| CLRC | Community Learning Resource Center |
| DACE | Directorate of Adult and Continuing Education |
| DEA | Data Envelopment Analysis |
| DLP | Digital Literacy Programme |
| EARCs | Education Assessment and Resource Centres |
| ECDE | Early Childhood Education |
| EFA | Education for All |
| FBOs | Faith-Based Organizations |
| PISA | Program for International Student Assessment |
| PLP | Primary Literacy Program |
| MOE | Ministry of Education |
| MDTIs | Multipurpose Development Training Institutes |
| MPET | Master Plan on Education and Training |
| NESSP | National Education Sector Strategic Plan |
| SDG | Sustainable Development Goals |
| TIQET | Totally Integrated Quality Education and Training |
| UIL | UNESCO Institute for Lifelong Learning |
| UN | United Nations |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |

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# 1. Introduction

Education is a fundamental human right and a core pillar in attainment of sustainable development. The UN 2030 agenda of Sustainable Development Goal 4 aims to promote inclusivity and reduce inequalities through access to quality education and fostering of lifelong learning opportunities for all. Encompassing lifelong learning clearly outlines the role adult education plays in achieving both global and national education agenda and policies (Elfert, 2019). In addition, the commitment reiterates provision of quality education and improving learning outcomes which can be achieved through bolstering inputs and evaluating outcomes to measure milestones.

The Adult and Continuing Education (ACEs) initiative caters to individuals who have never experienced formal education or had to discontinue their studies due to various circumstances, like poverty or limited access to schooling (MOE, 2012). Historically, such educational opportunities were not accessible to adults. Nevertheless, the ACE program has emerged as a comparable alternative to basic formal education, ensuring that out of school youth, marginalized communities and adult participants acquire skills and knowledge equivalent to high school graduates.

Despite the education sector being granted the highest proportion of the Kenya's national budget, securing a total of Sh628.6 billion for the fiscal year 2023-24 corresponding to 27.4 percent of the projected national spending, the directorate of ACE remains significantly underfunded (MOE, 2023) hence assessing optimal utilization of the limited resources by the directorate is critical. Generally, the ACE programme has been receiving less than 1% of the total Ministry's budget which is much below the internationally recommended benchmark of at least 3%. Table below shows the funding levels for the Directorate in the last 5 financial years.

**Table 1.1: Proportion of ACE Funding against Ministry's Total allocation**

| Financial Year | MoE Budget Allocation (Ksh million) | DACE Budget Allocation (Ksh million) | Percentage of Ministry's Budget |
|---|---|---|---|
| 2017/2018 | 416,000 | 971.4 | 0.23% |
| 2018/2019 | 494,800 | 1010.7 | 0.20% |
| 2019/2020 | 473,400 | 1133.0 | 0.24% |
| 2020/2021 | 505,200 | 960.9 | 0.19% |
| 2021/2022 | 503,900 | 801.6 | 0.16% |

*Source: MOE*

Since its establishment in 1979, the Department of Adult Education, which later evolved into the Directorate of Adult and Continuing Education in 2009, has experienced transitions across various government ministries. It began under the Ministry of Labour and Social Services in April 1979, then moved successively through six (transferred between eight distinct ministries) other ministries until it found its current home in the Ministry of Education in March 2008. These shifts have had an impact on the Directorate's allocation of resources and its local visibility. This also explains why the program remained unfamiliar to many, as it lacked a clear affiliation with a specific ministry.

The study investigates the technical efficiency of adult and continuing education centres to ascertain the performance of the various decision-making units and understand what factors affect their efficiency. Kenya's vision 2030 framework is aiming to become a middle-income country by achieving a 90% adult literacy rate compared to current national literacy level of 82.4% (Economic Survey, 2023). However, the ASALs region in Kenya, which comprises arid and semi-arid areas and covering 89% of Kenya landmass, faces challenges in achieving this goal (Ministry of Education, 2019). The literacy levels in the Arid and Semi-Arid Lands (ASALs) region of Kenya are significantly lower compared to non-ASAL regions with 90% of the 2 million Kenyan children who have never attended school residing in these areas (MOE, 2019). This poses a substantial challenge to the overall educational development and socio-economic progress of the ASALs population. Harsh climatic conditions, limited infrastructure, and socio-economic disparities have also hindered the effectiveness of educational initiatives by the government and other institutions. As a result, access to quality education is limited and dropout rates are high, leading to low literacy levels (Munene and Sara, 2015). Introduction of ACEs remains an alternative to cater for the marginalized, out of school youth and adults.

While there are existing policies aimed at addressing participation in Adult and Continuing Education (ACE) centres, the focus on efficiently utilizing the allocated resources in the adult education sector has been insufficient, especially in ASALs. Therefore, it is essential to evaluate the efficiency of education resources in Kenya directed towards DACE, especially considering the limited resources available to achieve the desired outcomes. It is vital to determine optimal operational levels to reduce unnecessary expenditures within the Directorate. Therefore, this paper will provide greater awareness of the benefit of the assessment in efficiency of the resources devoted to Adult and Continuing Education Centres to ensure each dollar spent on adult education produces the highest possible level of student achievement.

To address the problem of low adult literacy in the ASAL regions, the study focuses on two objectives aimed at determining the extent to which Adult and Continuing Education Centres (ACEs) are utilizing available resources to produce maximum outputs. Specifically, the study seeks to:

i) Estimate the technical efficiency of Adult and Continuing Education Centres (ACEs) within the ASALs region in Kenya.

ii) Determine factors that influence efficiency levels in ASALs region.

The rest of the paper is structured as follows: Section 2 discusses the situation of ACEs in Kenya, its policy and regulatory framework. Section 3 explores the theoretical and empirical foundations underpinning the study, section 4 explains the methodology including descriptions of the DEA framework under consideration, the steps involved in calculating the technical efficiency and factors influencing the efficiency scores, and comprehensive overview of the data sources. Section 5 discusses the study's findings, while conclusions and policy recommendations are presented in section 6.

# 2. Situation Analysis of ACE in Kenya

## 2.1 Policy Legal and regulatory framework Governing ACE

The constitution of Kenya (2010) takes cognizance of the right to basic education for all its citizens and emphasizes on the vitality of taking affirmative actions to ensure the youth have access to education and relevant training. Aligned with the country's developmental blueprint, Kenya Vision 2030, ACE's significance lies in equipping individuals with the knowledge, skills, and attitudes necessary to implement the initiatives outlined in its pillars. Notably, the Medium-Term plan for Kenya Vision 2030 aims to increase adult literacy rate to 90%. To achieve this, there is a commitment to expanding ACE provision across the 47 counties while ensuring its alignment with the learners' needs.

Illustrating the government's dedication to ACE advancement, the Board of Adult Education was established through a parliamentary enactment in 1966, as part of the commitment to achieve education for adult and out of school youth. This board was entrusted with the task of developing, advising, and overseeing ACE activities in the country. Additionally, the success in delivering ACE has been supported by its integration into various other educational policy documents. Notably, a series of policy papers spanning from 1997 to the present day highlighting the significance of ACE. Examples of the policy papers include the Master Plan on Education and Training (MPET) 1997–2010, the 1999 report on Totally Integrated Quality Education and Training (TIQET), Poverty Reduction Strategy Paper (PRSP) 2001-2003, Economic Recovery Strategy for Wealth and Employment (ERSWEC) 2003-2007, and Sessional Paper No. 1 of 2005 addressing a Policy Framework for Education, Training, and Research (Nyatuka & Ndiku, 2015).

Other significant policy documents relevant to ACE include the Kenya Education Sector Support Programme (KESSP) 2005-2010, the National Youth Policy for Polytechnics (2007), the Policy Paper on Adult and Continuing Education (2007), and the Gender Policy in Education (2007). The Constitution of Kenya unequivocally establishes basic education as an inherent human entitlement (COK, 2010). In alignment with this constitutional mandate, the Basic Education Act (2013) was introduced to govern the provision of fundamental education, including ACE, pre-primary, primary, secondary, and special needs education. The Fifth Schedule of the Act designates the creation of a dedicated ACE board with responsibilities ranging from advising the Cabinet Secretary (CS) accountable for education on ACE-related matters to coordinating and regulating ACE providers, including institutions, while also identifying and evaluating requirements for ACE growth (2013).

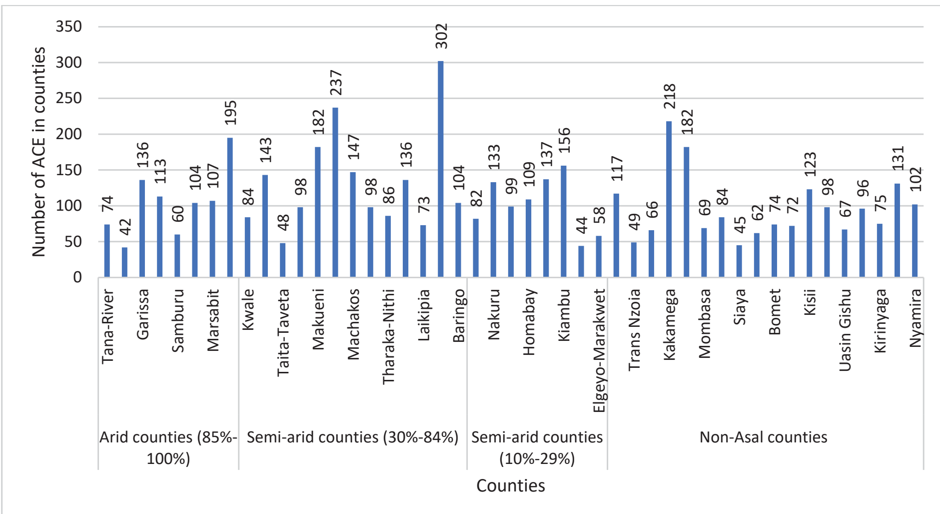
The ACE board's additional responsibilities include promoting ACE activities, providing annual progress reports to the Cabinet Secretary (CS) and offering guidance to the National Education Board on ACE matters. At the county level, the County Education Committee is tasked with advising the County Education Board on ACE activities. The goals of ACE, according to COK (2010) are multifaceted:

tackling illiteracy, preparing learners for global citizenship, nurturing diverse literacy, fostering the acquisition of vital knowledge, skills, and attitudes to adapt to emerging technologies and production skills. Further objectives involve nurturing self-esteem, values, and desirable conduct; increasing ACE and lifelong learning access, engagement, and continuation; and training local personnel for rural development through participatory, integrated approaches using multi-purpose training institutes.

This section examines the count of ACE centers for ACE programs in the year 2020. The number of ACE centres experienced a gradual decline from 2018 to 2019 and 2020 reaching 5340, 5161 and 4932 in the respective years. This shows a 4.4 per cent decline from 2019 to 2020 which can be attributed to the departure of volunteer instructors from the ACE program and the completion of projects sponsored by community-based organizations (CBOs) and faith-based organizations (FBOs) (MOE, 2020).

The following figure displays the distribution of ACE centers across the counties. West Pokot, Nairobi City, and Kitui emerged with the highest number of centers, while Lamu, Isiolo, Tharaka Nithi, Tana River, and Mombasa had the lowest number of ACE centers.

**Figure 2.1: Adult and Continuing Education Centers**




*Data Source: MOE, Basic Education Statistical Booklet, 2020*

## 2.2 Status of ACEs in Kenya

In 1979 the Directorate of Adult and Continuing Education (DACE) was established whose main mandate is provision of Adult and Continuing Education to out-of-school youths and adults. To fulfil its mandate, the Directorate administers various essential programs, including the Basic Literacy Programme, Post Literacy Programme, and Continuing Education initiatives. In terms of policy, the Directorate is actively involved in shaping the landscape of Adult and Continuing Education in Kenya. This includes formulating policies that address vital aspects such as Adult and Continuing Education Policy, Literacy Assessment and Measurement, and the National Qualification Framework. Through these policies, the Directorate seeks to create a conducive environment for learning, skill development, and educational advancement among adults. The Adult and Continuing Education Directorate therefore offers fundamental literacy and ongoing education to young individuals and adults who are not attending formal school.

The main programs offered under the ACEs include ABE (Adult and Basic Education), CLRC (Community Learning Resource Center), DLP (Digital Literacy Program), EARCs (Education Assessment and Resource Centres), PLP (Primary Literacy Program), MPDTIs (Multipurpose Development Training Institutes) and primary and secondary schools' collaborations. The target audience for Kenya's Directorate of Adult and Continuing Education (DACE) include adults without formal education, those with limited educational attainment, out-of-school youth, individuals seeking professional development, lifelong learners, and special interest groups like women, the elderly, persons with disabilities, and marginalized communities. DACE's mission is to offer flexible and accessible learning opportunities, enabling diverse groups to continue their education, enhance skills, and expand knowledge.

Evaluating the effectiveness of the ACEs aligns with Kenya's constitution, the Public Finance Act, and the Public Finance Management Act of 2015, all emphasizing prudent public resource management. Additionally, the efficiency of the education system harmonizes with the goals of Vision 2030, which seeks to enhance public service delivery by advancing administrative frameworks. This study's primary aim is to assess the efficiency of adult and continuing education centers (ACEs) in Kenya and subsequently offer policy recommendations for enhancing the ACEs' efficiency.

# 3. Literature Review

## 3.1 Theoretical Literature

The theories anchoring this study were aligned with the objectives of the study and they include:

### *3.1.1 Production Theory*

The fundamental concept underlying the theory of technical efficiency is based in the theory of production. This theory posits that the quantity of output a firm can generate is determined by the quantity of inputs it utilizes in its production process. This relationship can be mathematically represented using a linear functional form as follows:

$$Q = f\,(X_1, X_2 \,\ldots\ldots\ldots\ldots\, X_n)$$

Q represents the volume of a company's output, while $X_1$, $X_2$, and $X_n$ denote the quantities of inputs utilized in the process of producing Q. Within the realm of education, inputs are transformed into a variety of outputs through the process of teaching and learning. Various scholars, such as Coleman (1966), Mincer (1970), and Psacharopoulos and Patrinos (2004), have employed production theory to generate different outcomes using different inputs. For instance, they have used measures like school attainment to gauge individual skill development. Schultz (1961) and Becker (1962) emphasized the significance of incorporating the production process into schooling to attain the intended benefits of education. Typical inputs used in this context encompass factors like parental characteristics, socio-economic conditions, teacher qualities, and student characteristics. As per Farrel's perspective in 1957, efficiency pertains to a decision-making unit's capacity to generate the optimum achievable output utilizing a predetermined set of inputs. Consequently, technical inefficiency quantifies the extent to which inputs could be decreased without reducing the overall output.

The fundamental concept of technical efficiency is based on the theory of production. The theory underlies the principle of attaining economic efficiency. Education production efficiency expresses the ratio between educational input factors and the level of output for each unit of production.

Y=f(A,K,L) where A is level of technology, K is capital input, L is labour input.

Recognizing the significance of human errors in the production process and the intricate nature of production itself, Farrel (1957) contended that setting an exact theoretical maximum production level is a challenging endeavor. Hence, he proposed that efficiency could be better assessed by comparing a firm's performance against the optimal achievement of a similar unit. This concept laid the foundation for Data Envelopment Analysis (DEA). Introduced by Charnes, Cooper, and Rhodes in 1978, DEA is a linear programming method employed to gauge the relative efficiency of an organization. It is widely utilized for assessing technical efficiency, especially in scenarios where multiple production factors are at play and a single firm generates various outputs. Another technique employed to evaluate technical efficiency is Stochastic Frontier Analysis (SFA), a regression approach that incorporates an error term in the production frontier to represent technical inefficiency and random errors.

### *3.1.2 Human Capital Theory*

Human capital theory posits that investing in education is essential for acquiring skills and training that enhance an individual's capital (Blundell et al., 1999). In this regard, Tan (2014) contends that such knowledge and skills will enhance one's productivity in the workplace, leading to higher salaries since wages are ideally determined by productivity. Consequently, people would invest in education to a point where private benefits are equal to private costs. This concept of the knowledge economy is becoming globalized, with countries espousing that investing in education is the path towards accumulating human capital and ending poverty (World Bank, 2018).

The human capital approach to productive efficiency postulates that education can improve workers' capacity to understand and analyse market information, enabling them to make better decisions during state of economic disequilibria (Schultz, 1975). Additionally, education investment can enhance allocative choices and workers' productivity skills (Welch, 1970). Returns on education are high when useful learning opportunities can be taken advantage of. Rosenzweig (1995) asserts that these opportunities often come with new technologies, changes in the market, climatic changes, under-resourced marginalized areas, and political systems. Converting inputs to outputs through teaching and learning process and interaction with environmental variables will influence the significance of each standardized dependent variable on the literacy skills, employability, and per capita income of the ASALs residents.

## 3.2 Empirical Literature

Researchers worldwide have extensively investigated the efficiency of primary, secondary, and tertiary education systems, while comparatively less attention has been directed towards analyzing the efficiency of adult, non-formal, and informal education systems. ACE is among the various alternative learning programs being financed by the Kenya government. However, the efficient utilization of the resources directed to the directorate is largely unexplored. This study seeks to analyze the technical efficiency of ACE in ASALs region of Kenya.

Using Data Envelopment Analysis (DEA), Kirjavainen and Loikkanent (1998) conducted a study on the efficiency differences among Finnish senior secondary schools. Four model variations were employed, with average efficiencies ranging from 82% to 84%. When parents' educational level was introduced as an additional input, average efficiency improved to 91%. Augmenting simple quantitative inputs with teacher quality and matriculation results altered school efficiency rankings. Following DEA, a Tobit analysis was used to explain inefficiency, revealing that schools with small classes and diverse student bodies exhibited inefficiency, while school size had no impact. Surprisingly, private schools were relatively inefficient compared to public schools. Parental educational levels positively influenced efficiency when included in the Tobit model. The findings highlight avenues for enhancing senior secondary school efficiency in Finland.

Agasisti and Zoido (2019) conducted a study analyzing school efficiency in developing countries using OECD Program for International Student Assessment (PISA) 2012 data. They employed a two-stage Data Envelopment Analysis on over 6800 schools from 28 nations. Results indicated an average efficiency of around 70%, suggesting a potential 30% improvement in achievement scores through better resource utilization. Heterogeneity was evident both between and within countries, with higher efficiency scores found when comparing schools within the same country. Key influencers of school efficiency include student population attributes and educational resource quality. Additionally, teacher-related climate factors and perceived competition show positive correlations with heightened efficiency levels. Student characteristics were significant, with factors like motivation and truancy impacting efficiency. The study recommended practices like accountability, teacher involvement, professional development, and extracurricular activities to enhance efficiency levels.

Henriques & Marcenaro-Gutierrez (2021) conducted a study on the efficiency of secondary schools in Portugal using a hybrid Data Envelopment Analysis (DEA) approach. They assessed inputs like teachers, administrative staff, average socio-economic status, student-teacher ratios, and educational material shortages and outputs such as student completion rates average scores in mathematics, reading, and science, as well as other contextual factors, on a school-specific basis. Robustness test enabled decision-makers to grasp the responsiveness of each Decision-Making Unit's (DMU) efficiency to fluctuations in data. The DEA model helped gauge how alterations in measurements within-school diversity (such as test scores and the socio-economic status of students, having multiple observations per school) might impact the efficiency scores of efficient DMUs. Their findings showed that while average efficient public schools outperformed national counterparts in various competences, they fell short of OECD averages. Inefficiencies were observed in schools with low scores, particularly in reading.

Tran (2021) studied the efficiency of Australian Vocational Education and Training (VET) sector over the period 2008 to 2012 using dynamic network DEA model. The study focused on VET institutions as the primary decision-making unit which were evaluated through a two phases analysis: the teaching phase and industry responsiveness phase. In the teaching phase the primary objective was to assess the effectiveness of training students with key performance indicators being completion rate and industry satisfaction. These indicators in turn act as inputs in the industry as qualified work force/employer. The findings of the study depict the overall training efficiency on average was 0.835 while the mean divisional efficiencies for the two phases, teaching and industry responsiveness were 0.763

and 0.908 respectively. Evidently, the teaching phase exhibited comparatively lower efficiency levels hence need to improve by 23.7% through focusing on student enrolment management and delivery of quality education which are vital in elevating completion rates which will ultimately contribute to more efficient VET education system.

The study by Delprato and Antequera (2021) focused on assessing technical efficiency in both public and private schools in Latin America using Data Envelopment Analysis (DEA). The research revealed potential efficiency improvements of 12% for private schools and 18% for public schools in the region. Notably, the efficiency gap between the most and least efficient schools was more pronounced among public schools. Analyzing data from 705 schools in Ecuador, Guatemala, Honduras, and Paraguay, the findings indicate that private schools have a higher efficiency score of 0.88 compared to public schools with a score of 0.82. The study suggests that enhancing inclusion and equality could enhance efficiency for both school types. The study recommends reducing inequality and providing remedial classes in public schools to further improve their efficiency.

A study conducted by Horrace, Rothbart, and Yang (2022) focused on the technical efficiency of public middle schools in New York City. They employed panel data and a "true" fixed effect stochastic frontier model to estimate persistent and transient technical inefficiency in mathematics (Math) and English Language Arts (ELA) test score gains from 2014 to 2016. Their analysis revealed that around 58% of New York City middle schools exhibited efficiency in Math gains, while only 16% demonstrated efficiency in ELA gains. Multivariate inference techniques were used to identify subsets of efficient schools, providing policymakers with actionable decision rules for resource allocation and incentives. Notably, the study found that student composition significantly influenced ELA gains, while teacher composition impacted Math gains. This suggests that tailored interventions could enhance educational outcomes in public middle schools, aligning with the distinct needs of each subject area.

Stumbriene et.al (2022) conducted an efficiency and effectiveness analysis based on educational inclusion and fairness of 26 European countries using the data envelopment analysis. Their input indicators being accessibility of the system, ratio of teachers per 100 students and infrastructure, expenditure per student and teaching quality measured by learning hours while their desired output indicators were graduation rates, number of enrolled students and participation in the various level of education and undesired outputs were inequality index, early leavers from education and standard deviation of PISA scores. Their analysis indicated that the countries do not follow the set policy framework for inclusiveness and fairness for the key stages of education however, the minimum effectiveness estimates were higher than 0.81 for early childhood education, primary education and upper secondary education and above 0.73 for lower secondary education hence narrowly scattered while the minimum efficiency scores were lower for tertiary education with the estimates starting from 0.47 which indicated heterogeneity of tertiary education compared to the other levels of education. This shows there is room for improvement in tertiary education for majority of the countries examined.

### *Overview of Empirical Literature*

The empirical literature provides analysis of educational system efficiency, with a greater focus on primary, secondary, and tertiary education. However, there's been a relative increase of attention towards adult, non-formal, and informal education systems, to align with this study on Adult and Continuing Education (ACE) in ASAL regions of Kenya. The studies employed Data Envelopment Analysis (DEA) in combination of other sophisticated methodologies to evaluate efficiency. They revealed potential for substantial improvements in achievement scores through enhanced resource utilization. Key factors influencing efficiency included teacher quality, student characteristics, and institutional attributes. The studies emphasized the need for specific interventions, accountability measures, and strategic resource allocation to optimize educational outcomes. These findings collectively highlight the significance of evaluating and enhancing educational system efficiency for improved learning outcomes and societal development.

# 4. Methodology

This section highlights the theoretical framework underpinning the study, a detailed explanation of the DEA framework in calculating efficiency, choice of inputs and outputs, the various data sources, and drivers of efficiency.

## 4.1 Theoretical Framework

The literature review reveals that several factors influence efficiency in the education sector. Efficiency refers to a production system's ability to achieve higher output with a given set of inputs or to achieve a specific output using fewer inputs (Kumbhaker and Lovell, 2000). Although Adult and Continuing Education Centres (ACE) may not operate like profit-maximizing firms, they are considered production units in this context. To measure efficiency, empirical studies have commonly employed Data Envelopment Analysis (DEA), a non-parametric method used for evaluating the efficiency of homogenous organization units referred to as Decision-Making Units (DMUs), initially introduced by Charnes, Cooper, and Rhodes (2007).

DEA determines the most efficient Decision-Making Unit (DMU) within the sample by utilizing a combination of inputs and outputs to establish the production possibility frontier. This estimation of performance is derived from the DMU's ability to effectively utilize existing resources to achieve the optimal output. As a result, efficiency is represented as a ratio of the DMU's total outputs to its total inputs, which is equated as follows:

$$Productivity = Outputs/Inputs$$

The conceptualization entails the national government, working through county governments, providing various inputs such as budgetary allocation, enrolment into ACE centres, graduation rate, student teacher ratio, feeding programs, budgetary allocations to the specific ACE centres, Percentage of Private Enrolment, examination scores, scores in language and/or mathematics examinations, completion rates or Number of students awarded certificates to all Adult and Continuing Education Centres in Kenya. In this context, the Decision-Making Units (DMUs) are represented by county governments, which utilize these inputs through the teaching and learning process, and also interact with environmental factors to achieve the desired education outputs, ultimately leading to improved literacy levels.

The theory of production underlies the principle of attaining economic efficiency, in our case which is ensuring access to quality education, as it posits that the amount of output a system can produce depends on the number of inputs it employs. The theory is pegged on the idea firms aim to produce maximum output with minimum resources to achieve the set production goals. The production function is represented as below:

$$Q = f(X_1, X_2, \ldots, X_n)$$

DEA technique formulates an educational production function, if each decision-making unit (DMU) such as alternative learning program at county level, transforms inputs into outputs through a production process (Worthington, 2001). The technique calculates the technical efficiency of these DMUs by comparing their performance to an estimated frontier, which represents the highest possible output achievable given the available resources.

There are various forms of production function in which Q represents a firm's output, and $X_1$, $X_2$, and $X_n$ represent the inputs used to produce Q. An example is Cobb-Douglas production function that expresses the relationship between output and two inputs, capital, and labour. The Leontief production function uses inputs in fixed proportions. In the education literacy levels in ASALs regions context, the inputs are transformed to generate a range of outputs through the interaction of inputs, outputs and environmental factors. Education is a productive asset that can lead to increased human capital and, in turn, contribute to economic growth and development. The theory suggests that access to quality education is essential for individuals to acquire the necessary knowledge and skills to participate fully in society and the economy.

### *Estimating efficiency scores*

Measuring the efficiency score of adult and continuing education centres is important to assess utilization of learning resources to boost literacy levels. However, evaluating the efficiency of learning institutions is challenging. Frontier methods are commonly employed to estimate efficiency. The two approaches considered include Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA).

DEA refers to a non-parametric technique that employs linear programming to generate efficiency frontier, then computation of the efficiency scores is conducted relative to the frontier. The DEA approach is widely popular with studies on technical efficiency of literacy (Guan & Chan, 2012). The method is preferred since it doesn't require specification of distributional or functional forms for errors and may be used for multi-input and multi-out variables.

The Stochastic Frontier Analysis is rarely employed since it uses econometrics to estimate production and costs and therefore, have limited flexibility (Wang and Zhang, 2019). The technique is widely criticized for pre-determining the functional form of estimating efficiency of a Decision-Making unit (DMU).

Therefore, the study will employ the DEA technique to estimate efficiency scores of Adult and Continuing Education in Counties of Kenya.

### *DEA Framework*

In a county where multiple inputs X are used to produce multiple outputs Y, the technical efficiency of a decision-making unit (DMU), for example, Adult and Continuing Education Centre in a county can be expressed as:

$$E = (\sum^{r}_{(i=1)} U_r.Y_{rj}) / (\sum^{m}_{(i=1)} V_i.X_{ij})$$

Where;

$Y_{rj}$ = Refers to the quantity of *r* output produced by unit *j* in a county

$U_r$ = Refers to the weight attached to the output of *r* in a county

$X_{ij}$ = Refers to the quantity of *i* input produced by unit *j* in a county

$V_i$ = Refers to the weight attached to the output of *I* in a county

A linear programming technique is then employed to get efficiency levels for each DMU. At the optimal productivity, the level of output will be exactly equal to the input value based on the linear programming theorem. Efficiency is the firm productivity, which in this case is the ACEs centres disaggregated per county. Adult and Continuing Education Centres operate at optimal levels will have a unity efficiency scores, while counties without output will have a zero efficiency scores. Therefore, Efficiency score, E, lies within the range of zero and one.

$$E = (\sum^{r}_{(i=1)} U_r.Y_{rj}) / (\sum^{m}_{(i=1)} V_i.X_{ij}) \leq 1$$

## 4.2 Analytical Framework

The number of DMUs are assumed to be N, and each DMU has K inputs and M outputs. Therefore, $X_i$ will represent the vector of inputs while $Y_i$ will represent the vector of outputs. The DEA (Data Envelopment Analysis) will create a non-parametric frontier that demonstrates the distance between each DMU (Decision Making Unit) and the frontier itself. It will be defined as a ratio:

$$U' Y_i / V' X_i$$

Where U' and V' are output vectors and inputs weights, respectively.

To choose an optimal weight, the following mathematical problem is defined:

$$Max\ U,V\ (U'Y_i/V'X_i), \text{ subject to:}$$

$$U'Y_i/V'X_i \leq 1; \text{ for } j=1,2..n$$

$$u,v \geq 0$$

The solution to the above problem will assist in solving the values of *U* and *V*, that will ensure the efficiency measure of each DMU is maximized subject to the fact that all scores are less than or equal to one. However, an infinite number of solutions will be generated.

The constraint: V'xi=1, presented in the equation above is included to evade the situation. Therefore, we will restate the problem as follows:

$$Max\ U,V\ (u'yi),\ subject\ to$$

$$V^{\wedge}{}'\ Xi = 1$$

$$U'Yi - V'Xi \leq 0,\ i = 1,2......N$$

$$u,v \geq 0$$

This problem is run N times to generate the relative efficiency scores of all the DMUs.

### *Choice of DMUs and input/output indicators*

In Cai's study (2011), it is noted that the relative efficiency scores in the model are significantly influenced by the input and output indicators, as well as the number of DMUs included. If a frontier is constructed using a small number of DMUs, it may lead to all counties receiving scores of one, rendering the results potentially meaningless. To mitigate this issue, selection of all the 47 counties in Kenya has been made to ensure a more meaningful analysis. These counties have been classified as follows: Arid counties, with aridity levels ranging from 85% to 100%, experience severe water scarcity and limited agricultural potential, often relying on alternative livelihoods like pastoralism. Semi-arid counties, divided into two subcategories (30%-84% and 10%-29% aridity levels), face varying degrees of water stress, influencing their agricultural viability and land use patterns. Non-ASAL counties, characterized by aridity levels below 10%, enjoy more favorable climates and diverse ecosystems, making them suitable for a wide range of agricultural activities.

### *Measurement of efficiency*

Regarding education, technical efficiency pertains to the conversion of inputs, such as the quantity and quality of teachers, class availability, and educational resources, into a variety of outcomes through the educational process (Mincer, 1970; Psacharopoulos and Patrinos, 2004; Afonso et al., 2005). Efficiency can be categorized as output-oriented or input-oriented (Farrell, 1957). Output-oriented technical efficiency involves maximizing output based on a given set of inputs, while input-oriented technical efficiency focuses on minimizing inputs while achieving a particular level of output (Debreu, 1951; Charnes and Cooper, 1985).

The assessment of technical efficiency is widely employed. When applying the efficiency concept to education, the outcomes can encompass aspects such as numeracy, literacy levels, number of graduates and test scores. Consequently, this study draws upon efficiency and productivity theories to evaluate school performance, as they involve the transformation of inputs into outcomes (Coelli et al., 2005).

We considered environmental factors that could influence the technical efficiency of Adult and Continuing education centres.

**Table 4.1: Selected inputs and outputs**

| Variable | Measurement | Abbreviation | Data Source |
|---|---|---|---|
| **Input Indicators** | | | |
| Pupils-Teachers ratio | Measures the average number of teachers per student in a county | PTR | DACE |
| Per Capita Spending | Measures the average amount of money allocated and utilized by each student enrolled in ACE centers | PCS | DACE |
| Pupil-Textbook Ratio | Measures the average number of textbook per student in a county | PTB | DACE |
| ACE enrolment | Number of students enrolled into ACE centres | | DACE |
| **Output Indicators** | | | |
| Completion rate | Percentage of enrolled students who have graduated from ACE centres per county | CR | MOE statistical abstract 2019 |
| Performance scores | Scores achieved by graduates in ACEs centres per County | PS | MOE 2019 |

**Table 4.2: Environmental/Explanatory Variables**

| Variable | Measurement | Abbreviation | Data Source |
|---|---|---|---|
| Digital Literacy Programme | Digital Literacy Programme coverage in a county | DLP | MOE (2019) |
| Per Capita Income | GCP per county/Population per county (Ksh) | PCa | KNBS (Economic Survey) 2019 |
| ACE Sizes (standalone/ Integrated) | Type of adult and continuing education centres per county (Standalone/Integrated) | ACE | MOE Statistical abstract/ DACE |
| Location | location of the county Urban (1) Rural (0) | RurB | KNBS (Economic Survey) |
| Electricity | Electricity connectivity in ACE centres | ELN | MOE |
| Internet | Internet coverage in a county | ICN | MOE |

The constant return to scale (CRS), a model developed by Charnes et al., (1978), ensures output changes by similar proportion as the change in inputs and therefore the size and number of Adult and Continuing Education Centres (ACEs) in ASAL counties is irrelevant when efficiency is being measured, since all schools are assumed to operate at their best scale size. However, variable return to scale (VRS) related to size is an important factor in the analysis since it allows the ratio of input level to output level varies with the alternative learning programs resourced school size and therefore more binding. An intercept term was added by Banker et al., (1984) to model by Charnes et al., (1978) to investigate the returns to scale.

## 4.3 Data

The study used secondary data from various sources, including the Kenya National Bureau of Statistics (KNBS), the Directorate of Adult and Continuing Education (DACE), and the Ministry of Education's statistical abstracts. First, the technical efficiency scores were estimated using an output-oriented variable returns to scale framework using DEAP 2.1 software and there after regress the environmental variables with efficiency scores as dependent variable using Tobit model in Stata 16.0. A total of 47 counties categorized into 4 groups based on aridity was assessed.

| | |
|---|---|
| Inputs indicators | Pupils-Teachers Ratio, Pupil-Textbook ratio Enrolment into ACE, Per capita spending |
| Outputs Indicators | Completion rates, Performance scores |
| Environmental factors | Per capita Income, Digital Literacy Programme, Location, Number of ACE centres (Integrated/Standalone), Electricity, Internet, and number of ACE graduates |

## 4.4 Variable Descriptions

**Per Capita Income:** Per Capita income indicates the average income per individual in a county. Higher per capita income signifies more financial resources that can be allocated to education, leading to improved access and quality of the alternative learning program.

**Pupils-Teachers Ratio**: The ratio of students to teachers is for evaluating class sizes and the attention each student can receive. A lower ratio often indicates more personalized education.

**Number of ACE Centers**: The number of ACE centers reflects the geographical reach and accessibility of adult education services, which is relevant for assessing educational access.

**Digital Literacy Programme**: This input signifies efforts to enhance digital skills among learners and educators. It's relevant as digital literacy is increasingly important for educational success and participation in the modern workforce.

**School (area) location** is a determinant because urban schools can be operated at lower costs and still achieve higher scores.

**Number of ACE Graduates**: The count of graduates from ACE programs is relevant as it reflects the program's effectiveness in enabling learners to complete their courses.

**Completion Rate**: This output measures the percentage of students who successfully complete their ACE programs, indicating program effectiveness in terms of retention and completion.

**Performance Grade Scores**: Performance grade scores provide insight into the quality of education delivered by ACEs, indicating the level of knowledge and skills acquired by graduates.

## 4.5 Determinants of technical efficiency

In our analysis consisting of all 47 counties, we have computed technical efficiency scores to evaluate and compare efficiency levels based on aridity categorization and per each county. These scores are bounded between zero and one, signifying the effectiveness of counties in delivering educational services. To identify the factors contributing to the variability in efficiency levels across counties, we employ Tobit regression. This regression method is chosen due to the inherent constraints of efficiency scores, which cannot fall below zero or exceed one. Our regression model incorporates various explanatory variables and dummy variables. These variables account for factors, including the county's location as either urban or rural, internet connectivity, electricity coverage within the county, per capita income, number of ACE centres and number of ACE graduates from the centres. By utilizing this approach, our aim is to gain insights into how these factors influence the variations in technical efficiency across all 47 counties, providing valuable information about the determinants of educational performance.

## 4.6 Estimating the Drivers of Efficiency

Empirical studies such as Afzal, 2014; Cai, 2011; Ayisi et al., 2019, indicate various factors such as school infrastructure, teacher qualification, education system, governance (security index), and financial structure have been identified as significant determinants for improving literacy skills. However, it is important to note that the importance of these variables may vary in the selected counties being studied. To gain a deeper understanding of the significance of these variables in the ASALs region, further analysis is required. In this study, the Tobit regression model is utilized to examine the impact of these variables on the technical efficiency results of DEA VRS.

Several empirical studies have utilized the Tobit regression model as a second-stage analysis to examine the influence of environmental factors on efficiency scores (Nasierowski and Arcelus, 2013; Guan and Chen, 2012; Chen, Hu, and Yang, 2011; Afzal, 2014). The reason behind this approach is that DEA-generated scores typically fall within the range of 0 and 1 (Ji and Lee, 2010). As a result, using ordinary least squares (OLS) estimation alone may lead to inaccurate results.

The stochastic model underlying Tobit regression can be represented as:

$$Y_t = \beta x_i + \mu_i \text{ if } \beta x_i + \mu_i > 0$$

$$= 0 \text{ if } \beta x_i + \mu_i \leq 0$$

$$i = 1,2,3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots N$$

N is the number of observations, $Y_i$ is the dependent variable, $X_i$ is a vector of independent variables, $\mu_i$ is the independently distributed error term and β is a vector of coefficients.

The specific efficiency function for the literacy levels in ASALs region as a function of the ACEs of the selected counties can be written as:

$$E_i = \beta_0 + \beta_1 Digital\ Literacy\ Program + \beta_2 Location + \beta_3 PerCapita\ Income + \beta_4 Internet + \beta_5 Electricity + \beta_6 ACEs\ Centres + \dot{E}$$

In summary, a Tobit regression model was conducted to examine the factors influencing efficiency of adult and continuing education centres (ACE) in Kenya's ASAL counties. The efficiency scores were used as the dependent variable, and we considered various potential factors that could impact the efficiency of the ACE in a county. We identified six regression variables/environmental variables to evaluate their influence on ACEs grade and completion rate performance, as outlined by Orsini et al. (2012). To mitigate potential heteroscedasticity in the data, the variables GCP per capita and number of ACE graduates was logarithmized. Pairwise correlation was also conducted to identify variables which might be highly correlated to each other. Near linearly independent variables were selected.

## 4.7 Descriptive statistics

The table below is a summary of the descriptive statistics for the output and input variables and the potential drivers of efficiency.

**Table 4.3: Summary Descriptive Statistics**

| | Observation | | Mean | | Std. Deviation | | Minimum | | Maximum | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Non-ASAL | ASAL | Non-ASAL | ASAL | Non-ASAL | ASAL | Non-ASAL | ASAL | Non-ASAL | ASAL |
| Enrolment into ACE | 18 | 29 | 4324.17 | 4476.55 | 2704.07 | 2574.12 | 1537 | 736 | 13247 | 10267 |
| ACE Completion rate (2019) | 18 | 29 | 0.09 | 0.12 | 0.04 | 0.09 | 0.04 | 0.02 | 0.18 | 0.44 |
| Pupil Teacher Ratio | 18 | 29 | 56.71 | 56.03 | 26.41 | 33.98 | 21.83 | 13.29 | 120.82 | 162.97 |
| Per Capita Spending | 18 | 29 | 403.46 | 454.38 | 190.97 | 305.92 | 109.69 | 116.2 | 791.04 | 1310.73 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Per Capita Income | 18 | 29 | 193529.11 | 142795.5 | 118417.42 | 57662.65 | 93187.62 | 58857.1 | 588329.13 | 255076.6 |
| Location | 18 | 29 | 0.11 | 0 | 0.32 | 0 | 0 | 0 | 1 | 0 |
| Number of ACE graduates | 18 | 29 | 348.33 | 477.10 | 180.14 | 401.08 | 132 | 70 | 775 | 1703 |
| Internet | 18 | 29 | 13.79 | 11.42 | 9.07 | 8.16 | 7.2 | 3.5 | 42.1 | 39.1 |
| Digital Literacy Programme | 18 | 29 | 94.18 | 88.70 | 7.31 | 11.37 | 79.59 | 65 | 100 | 100 |
| Electricity | 18 | 29 | 45.69 | 34.81 | 22.56 | 20.35 | 19.7 | 8.6 | 96.5 | 91.7 |
| Pupils-Textbook Ratio | 18 | 29 | 0.96 | 0.97 | 0.06 | 0.11 | 0.82 | 0.5 | 1.06 | 1.18 |
| Performance Grades proficiency | 18 | 29 | 48.27 | 48.40 | 6.13 | 5.69 | 41.52 | 38.93 | 65.53 | 60.01 |

*Source: Author's Own Compilation*

The provided data presents descriptive statistics for various variables across different regions categorized as Arid, Semi-Arid, Semi-Arid, Non-Asal, and National. These regions are defined based on their aridity percentages. The key variables include per capita income, digital literacy program participation, completion rate in ACE, the number of ACE centres, ACE graduates and pupil teachers ratio.

**Descriptive Statistics Arid 85%-100%**

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Per capita | 8 | 86407.66 | 23632.21 | 58857.10 | 123342.43 |
| Digital Literacy Program | 8 | 81.13 | 11.22 | 67 | 98.74 |
| Completion rate in ACE | 8 | .08 | .05 | .02 | .16 |
| Number of ACE centers | 8 | 97.25 | 48.14 | 42 | 193 |
| ACE graduates | 8 | 310.13 | 301.85 | 70 | 1006 |
| Pupil Teachers Ratio | 8 | 50.63 | 17.78 | 29 | 80 |
| Pupil Classroom ratio | 8 | 43.39 | 15.13 | 30 | 76 |

*Source: Own Compilation*

The statistics show variations in these variables across the different regions, reflecting the diverse economic, educational, and infrastructural conditions. For instance, in the Arid region (85%-100% aridity), the per capita income is comparatively lower, indicating economic challenges, while internet access and digital literacy program participation are moderate. On the other hand, the Semi-Arid region (30%-84% aridity) exhibits higher per capita income, better internet access, and digital literacy program participation compared to Arid regions.

### Descriptive Statistics Semi-Arid 30-84%

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Per capita | 13 | 151209.19 | 42276.70 | 107300.49 | 228174.88 |
| Digital Literacy Program | 13 | 91.87 | 1 | | 100 |
| Completion rate in ACE | 13 | 0.118 | .088 | .024 | .37 |
| Number of ACE centers | 13 | 125.85 | | | 300 |
| ACE graduates | 13 | 594.85 | 47575 | | 1703 |
| Pupil Teachers Ratio | 13 | 34.538 | 10.541 | 23 | 53 |
| Pupil Classroom ratio | 13 | 34.231 | 8.197 | 24 | 48 |

*Source: Own Compilation*

### Descriptive Statistics (Semi-Arid 10%-29%)

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Per capita | 13 | 185510.94 | 61862.10 | 101644.95 | 255076.64 |
| Digital Literacy Program | 13 | 91.11 | 11.04 | 71 | 100 |
| Completion rate in ACE | 13 | .15 | .12 | .07 | .44 |
| Number of ACE centers | 13 | 93.75 | 30.49 | 42 | 138 |
| ACE graduates | 13 | 452.75 | 326.25 | 136 | 1200 |
| Pupil Teachers Ratio | 13 | 36.63 | 7.25 | 27 | 47 |
| Pupil Classroom ratio | 13 | 35.75 | 6.30 | 27 | 43 |

*Source: Own Compilation*

### Descriptive Statistics (Non-Asal)

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Per capita | 18 | 193529.11 | 118417.42 | 93187.62 | 588329.13 |
| Digital Literacy Program | 18 | 94.18 | 7.31 | 79.59 | 100 |
| Completion rate in ACE | 18 | .09 | .04 | .04 | .18 |
| Number of ACE centers | 18 | 97.61 | 46.81 | 45 | 252 |
| ACE graduates | 18 | 348.33 | 180.14 | 132 | 775 |
| Pupil Teachers Ratio | 18 | 39.72 | 8.14 | 30 | 56 |
| Pupil Classroom ratio | 18 | 36.28 | 10.34 | 24 | 60 |

*Source: Own Compilation*

In the Non-Asal region, which is presumably more favourable in terms of aridity, per capita income is higher, and most variables such as internet access and digital literacy program participation are also relatively better. The National statistics represent an average across all regions.

### Descriptive Statistics (National)

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Per capita | 1 | 197414.16 | 0 | 197414.16 | 197414.16 |
| Digital Literacy Program | 1 | 90.80 | 0 | 90.80 | 90.80 |
| Completion rate in ACE | 1 | .096 | 0 | .096 | .096 |
| Number of ACE centers | 1 | 108.87 | 0 | 108.87 | 108.87 |
| ACE graduates | 1 | 20106 | 0 | 20106 | 20106 |
| Pupil Teachers Ratio | 1 | 39.62 | 0 | 39.62 | 39.62 |
| Pupil Classroom ratio | 1 | 38.02 | 0 | 38.02 | 38.02 |

*Source: Own Compilation*

It was observed that there were significant differences in education indicators among ACE Centres in Kenya. For instance, the completion rate in ASALs region was notably higher compared to the non-ASALs region, with 14.7% in ASALs as opposed to 9.2% in non-ASALs, and 9.6% at the national level. Students in ASAL regions were more committed to adult education programs, possibly because formal education options were limited for them. Many may not have had the opportunity to attend school when they were younger, and so they prioritized adult education at a later age, leading to a higher survival rate.

Furthermore, enrolment numbers varied widely, ranging from 736 students to 13287 students in 2019. This discrepancy is also reflected in the Pupil-Teacher Ratio (which includes both Teacher Service Commission (TSC) teachers and non-TSC teachers at both primary and secondary levels). The lowest PTR was recorded in Arid regions at 34 students per teacher, while the highest was 39 students per teacher in non-ASAL counties, on average. Additionally, there were significant differences across schools in terms of pupil-textbook ratios and per capita spending ratios. This highlights the varying educational resources and environments across different ACE Centres.

## 4.8 Correlates of the ACE Education Performance and Completion

Table 4.4 presents a set of pairwise correlations between different variables associated with Adult and Continuing Education (ACEs).

**Table 4.2: Pairwise correlation of the ACE Education Performance and Completion**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| 1. Per capita | 1.000 | | | | | |
| 2. Digital Literacy Program | 0.508 | 1.000 | | | | |
| 3. Completion rate in ACE | 0.675 | 0.248 | 1.000 | | | |
| 4. ACE graduates | 0.076 | -0.209 | 0.149 | 1.000 | | |
| 5. Pupil Teachers Ratio | 0.315 | -0.468 | -0.052 | 0.322 | 1.000 | |
| 6. Pupil Classroom ratio | 0.139 | -0.426 | 0.073 | 0.378 | 0.924 | 1.000 |

*Source: Own Computation*

The per capita has a relatively weak correlations with the other ACE-related factors, suggesting that per capita income is not strongly associated with these educational metrics. Completion rate demonstrates a strong positive correlation of 0.675 with Per Capita, signifying that areas with higher per capita income levels tend to also have higher completion rates in ACE programs.

Completion Rate shows a robust correlation of 0.68 with Per Capita, underlining the importance of economic resources in achieving higher completion rates in ACE programs. This implies that regions with higher income levels may have more resources available for educational programs, leading to increased participation and successful completion. Pupil-Teacher Ratio displays a moderate negative correlation of -0.32 with Per Capita, indicating that areas with higher per capita income levels tend to have lower pupil-teacher ratios. This suggests a potential connection between economic resources and the availability of teachers.

Pupil Teacher Ratio indicates a negative correlation of -0.32 with Per Capita, suggesting that areas with higher per capita income levels tend to have lower pupil-teacher ratios. This shows regions with greater economic resources are better equipped to maintain lower class sizes for every teacher, potentially leading to more personalized and effective learning experiences.

# 5. Analysis and Findings

In this chapter, we discuss and present the findings of the study. First, we compute and tabulate the efficiency scores using Data Envelopment Analysis generated from DEAP 2.1 program software. These scores are categorized based on aridity of the counties and national level. Thereafter, we calculate the Tobit regression results in order to determine the factors influencing efficiency in Adult and Continuing Education Centres in ASALs using Stata 16.0 Software.

## 5.1 Technical Efficiency

The scores for technical efficiency were calculated assuming variable returns to scale (VRS). We used DEAP 2.1 program software to estimate Technical Efficiency. On average, the ACEs in each county could increase their output by 21.2 percent with the current level of inputs, as the mean technical efficiency score for the 47 counties is 78.8 percent. The overall technical efficiency of the 47 counties varies from 70 to 100 percent, with 21 of the sampled counties being technically efficient. This means these 21 counties are already operating at their maximum output level and would need more inputs to increase production. Table 5.1 below provides a summary of these scores based on arid categorization and counties.

**Table 5.1: Summary of VRS Efficiency scores by Aridity and Counties**

| Aridity | Total Number of counties | Mean Efficiency Scores | No. of counties in the 70-89% efficiency score range | No. of counties in the 90-99% efficiency score range | Technically efficient counties (100%) |
|---|---|---|---|---|---|
| Arid counties (85%-100%) | 8 | 0.963 | 1 | 1 | 6 |
| Semi-arid counties (30%-84%) | 13 | 0.919 | 5 | 2 | 6 |
| Semi-arid counties (10%-29%) | 8 | 0.921 | 3 | 2 | 3 |
| Non-Asal counties | 18 | 0.912 | 7 | 5 | 6 |
| National | 47 | 0.788 | 16 | 10 | 21 |

*Source: Own Computation*

For ASAL regions, which are further divided into Arid, Semi-arid (30%-84%), and Semi-arid (10%-29%), the mean efficiency scores are as follows: 0.963 for Arid, 0.919 for Semi-arid (30%-84%), and 0.921 for Semi-arid (10%-29%). Non-ASAL counties have a lower mean efficiency score of 0.912, indicating that they are generally less efficient in resource utilization compared to ASAL regions. The analysis revealed that the average technical efficiency among the 47 DMUs stood at 78.8 percent. These findings suggest that the existing provision of educational services through ACEs could be increased by up to 21.2 per cent without requiring additional resources for the ACEs.

### *Distribution of technical efficiency scores by aridity*

The data compiled and analyzed in this study was collected during the period when the country adopted a decentralized system of government following the enactment of the 2010 constitution of Kenya. In line with this, the nation was categorized according to the level of aridity in its counties. The technical efficiency scores for each of the 47 counties are then classified based on their respective aridity levels, as outlined in the subsequent tables.

**Table 5.2: Technical efficiency scores**

| **Arid counties (85%-100%)** | **CRS** | **VRS** |
|---|---|---|
| Tana-River | 0.914 | 1.000 |
| Isiolo | 1.000 | 1.000 |
| Garissa | 0.981 | 1.000 |
| Wajir | 0.969 | 0.974 |
| Samburu | 0.724 | 0.728 |
| Mandera | 0.996 | 1.000 |
| Marsabit | 1.000 | 1.000 |
| Turkana | 0.898 | 1.000 |
| **Mean Efficiency scores** | **0.935** | **0.963** |
| **Semi-Arid counties (30%-84%)** | | |
| Kwale | 0.950 | 1.000 |
| Kilifi | 0.852 | 0.870 |
| Taita-Taveta | 1.000 | 1.000 |
| Kajiado | 1.000 | 1.000 |
| Makueni | 0.831 | 0.851 |
| Kitui | 0.706 | 0.719 |
| Machakos | 0.865 | 0.876 |
| Embu | 1.000 | 1.000 |
| Tharaka-Nithi | 1.000 | 1.000 |
| Meru | 0.751 | 0.779 |
| Laikipia | 0.912 | 0.912 |
| West Pokot | 1.000 | 1.000 |
| Baringo | 0.822 | 0.945 |
| **Mean Efficiency scores** | **0.899** | **0.919** |
| **Semi-arid counties (10%-29%)** | | |
| Narok | 0.729 | 0.755 |
| Nakuru | 0.855 | 0.888 |
| Migori | 0.826 | 0.841 |
| Homabay | 0.933 | 0.936 |
| Nyeri | 0.934 | 0.953 |

| | | |
|---|---|---|
| Kiambu | 1.000 | 1.000 |
| Lamu | 1.000 | 1.000 |
| Elgeyo-Marakwet | 0.822 | 1.000 |
| **Mean Efficiency scores** | **0.887375** | **0.921625** |
| **Non-Asal counties** | | |
| Bungoma | 0.873 | 1.000 |
| Trans Nzoia | 0.959 | 1.000 |
| Busia | 0.782 | 0.800 |
| Kakamega | 0.870 | 0.926 |
| Nairobi | 1.000 | 1.000 |
| Mombasa | 1.000 | 1.000 |
| Kisumu | 0.899 | 0.919 |
| Siaya | 0.879 | 0.895 |
| Vihiga | 0.841 | 0.843 |
| Bomet | 0.790 | 0.793 |
| Kericho | 0.828 | 0.832 |
| Kisii | 0.685 | 0.769 |
| Nyandarua | 0.877 | 0.908 |
| Uasin Gishu | 0.884 | 0.902 |
| Nandi | 0.808 | 0.850 |
| Kirinyaga | 1.000 | 1.000 |
| Murang'a | 0.918 | 0.970 |
| Nyamira | 0.9996 | 1.000 |
| **Mean Efficiency scores** | **0.883** | **0.912** |
| **National** | **0.782** | **0.788** |
| **Mean National** | **0.896** | **0.921** |

*Source: Author's Own Compilation*

## 5.2 Determinants of efficiency of ACEs

The statistical analyses were conducted using STATA 16.0 statistical software. A Tobit model was chosen due to its estimation for left-censored data at 0. The Tobit model, as proposed by Schnedler (2005), proves to be a suitable tool in this context, given that efficiency scores are constrained and cannot fall below 0 or exceed 1. The Tobit model operates under the premise that it observes the variable only within defined boundaries. Should the value of an unobservable dependent variable fall outside these bounds, it is set to equal the limit value. Furthermore, to analyze the efficiency determinants of ACE schools in Kenya, we examined both institutional factors (under the control of ACE school management) and background factors (beyond the school's control). This study had also examined the efficiency of ACEs in Kenya, categorized by aridity levels, with the dependent variable being efficiency. The selected institutional and background factors served as independent variables. A Tobit regression model was employed to analyze the influencing factors on CCR and BCC efficiencies across counties. The results presented Tobit regression coefficients and their respective test outcomes. We identified six regression variables to evaluate their influence on ACEs grade and completion rate performance, as outlined by Orsini et al. (2012). To mitigate potential heteroscedasticity in the data, the variables GCP per capita and number of ACE graduates were logarithmized.

The results of the Tobit regression at National level, ASAL and Non-ASAL counties are displayed in Table 5.3

**Table 5.3: Tobit Regression Results in ASAL and NON-ASAL Counties**

| | Co-efficient | | |
|---|---|---|---|
| | **National** | **ASAL** | **NON-ASAL** |
| Per Capita | -0.033<br>(0.033) | -0.043<br>(0.039) | -0.030<br>(0.058) |
| ACE graduates | 0.017<br>(0.014) | 0.008<br>(0.016) | 0.061***<br>(0.022) |
| Internet | -0.005**<br>(0.003) | -0.010**<br>(0.004) | -0.010***<br>(0.004) |
| Digital Literacy Programme | -0.003**<br>(0.001) | -0.002*<br>(0.001) | -0.004**<br>(0.002) |
| Electricity | 0.004***<br>(0.001) | 0.006***<br>(0.002) | 0.005***<br>(0.001) |
| Location | 0.056<br>(0.052) | 0 | 0.137**<br>(0.063) |
| ACE | -0.0002<br>(0.0001) | -0.0003<br>(0.0002) | 0.0003<br>(0.0002) |
| Cons | 1.364<br>(0.371) | 1.510***<br>(0.433) | 1.188*<br>(0.684) |
| *Standard errors in parenthesis*<br>**** p<.01, ** p<.05, * p<.1* | | | |

*Source: Author's Own Compilation*

At national Level, the Tobit regression results reveal that three variables, namely digital literacy program, internet connectivity, and electricity, are statistically significant at the 5% level. Although the per capita spending variable is not statistically significant, it shows the expected positive effect on the technical efficiency of Adult and Continuing Education Centres in the counties. For instance, a 1% increase in internet connectivity has the potential to move a county towards the efficient frontier. This is because in the context of adult education, internet connectivity enables access to various educational resources, including Massive Open Online Courses (MOOCs). The integration of MOOCs into basic education contexts can blend formal, non-formal, and informal learning experiences, leading to enhanced educational opportunities. The study's results support the research by Galor (2005), which suggests that investing in human capital through education plays a significant role in a country's transformation from imitation to innovation. Enhancing ICT infrastructure, as indicated by an increase in internet connectivity, is found to positively influence education efficiency, in line with the findings of Cai (2011) on the importance of ICT in supporting the diffusion of knowledge and technology in the economy.

Specifically, at national level, electricity emerged as a highly significant determinant, with a coefficient of 0.0038, indicating a positive impact on efficiency. Internet access was a significant factor at a 10% significance level. Engagement in digital literacy programs had a modest negative impact at a 5% significance level. These findings show the critical role of electricity, internet access, and digital literacy programs, in enhancing ACE school efficiency in Kenya. The findings of this study align with previous research conducted by Cherchye et al. (2010), which emphasized the importance of financial stability in improving the efficiency and effectiveness of education in low and middle-income countries. Similar agreement is observed with the studies by Cordero et al. (2017) and Kantabutra (2009), highlighting how the school's area and location can impact education efficiency, with urban schools showing higher scores and lower operating costs.

In ASAL regions, electricity emerged as a significant variable, with a positive coefficient of 0.0060301 on efficiency score. Other significant factors include internet access and participation in digital literacy programs at a 10% significance level.

In Non-ASAL regions, ACE graduates had a highly positive effect (coefficient: 0.061) at a 1% significance level. Access to electricity also played a critical role, with a positive coefficient of 0.0048. Location was also a significant variable, positively influencing efficiency scores with a coefficient of 0.137 at a 5% significance level.

The study analysed the significance of each potential factor affecting efficiency levels based on aridity levels as shown below.

**Table 5.4: Tobit Regression Results in ASAL Counties based on aridity levels**

| | Co-efficient | | |
|---|---|---|---|
| | **Arid Counties** | **Semi-arid (10%-29%)** | **Semi-arid (30%-80%)** |
| Per Capita | 0.283*** (0.014) | 0.768*** (0.037) | -0.103 (0.090) |
| ACE graduates | 0.083*** (0.004) | -0.049*** (0.007) | -0.021 (0.024) |
| Internet | -0.073*** (0.0029) | 0.0176*** (0.0016) | -0.0081 (0.0081) |
| Digital Literacy Programme | -0.002*** (0.0003) | -0.0181*** (0.0009) | -0.0042** (0.0018) |

| | | | |
|---|---|---|---|
| Electricity | 0.014 (0.0006) | -0.008*** (0.0009) | 0.006 (0.004) |
| Location | 0 (0.0001) | | |
| ACE Size | 0.000 (0.0001) | -0.0001 (0.0001) | -0.0003 (0.0002) |
| Cons | -2.448*** (0.168) | -6.304*** (0.392) | 2.557** (1.086) |
| *Standard errors in parenthesis*<br>**** p<.01, ** p<.05, * p<.1* | | | |

*Source: Author's Own Compilation*

In arid regions, per capita income, ACE graduates, internet access, digital literacy programs, and electricity significantly influenced ACE school efficiency scores at a 1% significance level. Per capita income had a strong positive effect (coefficient: 0.283). ACE graduates and electricity also showed positive effects (coefficients: 0.083 and 0.0138, respectively).

In semi-arid regions (10%-29% aridity), various factors significantly influenced ACE school efficiency scores. Per capita income, ACE graduates, internet access, digital literacy programs, and electricity all showed strong effects on efficiency at a 1% significance level.

In semi-arid regions (30%-80% aridity), the factors influencing ACE school efficiency were assessed. Per capita income, ACE graduates, internet access, digital literacy programs, and electricity showed no significant impact on efficiency scores. The economic resources and digital infrastructure may not be the primary drivers of educational efficiency in semi-arid areas with higher aridity levels.

The generated p-values in ASAL regions reveal that the independent variables have a significant influence on the computed school efficiency scores. Specifically, the coefficient for ACE size, as quantified by gross enrolment, have a positive value of 0.0080, signifying its significance at the 95 percent confidence level. This indicates that a one-point increase in school size is projected to lead to a 0.008 percentage point increase in the technical efficiency score. This indicate that larger schools demonstrate higher levels of efficiency, potentially attributed to the presence of economies of scale. This implies that larger schools can absorb overhead and administrative costs more effectively, resulting in lower marginal costs and optimal utilization of available resources. These findings align with previous technical efficiency studies mentioned in the literature review, underscoring that larger schools tend to operate more efficiently compared to their smaller counterparts (as observed in studies by Kirjavainen and Loikkanent, 1996; Kanina, 2012; and Kinara, 2014).

Another environmental variable examined was the geographical location of the school in non-ASAL regions. The results indicate that urban schools exhibit a positive coefficient of 0.137. However, this coefficient, although positive, is statistically significant at 5% level of significance. This suggests that, while urban-based schools may have slightly higher technical efficiency compared to their rural counterparts, this difference does reach a level of statistical significance. This observation aligns with the notion that socio-economic factors play a substantial role in determining efficiency. Additionally, urban schools are typically situated near social amenities, making them easily accessible and highly favored by students and families. This discovery is consistent with the existing literature, which consistently suggests that schools in urban areas tend to operate more efficiently compared to their rural counterparts. These findings are in line with the results reported by Zulal (2012).

The enrolment of students into Adult and Continuing Education (ACEs) indicated by ACE size showed a positive coefficient of 0.008, which is statistically significant at the 5% level. This suggests that higher enrolment is linked with greater efficiency. In other words, higher enrolment levels are associated with better performance in terms of efficiency.

# 6. Conclusions and Policy Recommendations

## 6.1 Conclusion

Education serves as an important tool for driving the social and economic development of a nation. Therefore, it is imperative that investments in this sector yield the highest possible returns. This study focuses on assessing the Technical Efficiency of ACE Centres in Kenya, examined on a county-wide scale. The primary objectives were to assess the efficiency levels of these educational institutions and to identify potential sources of inefficiency. The study utilized various inputs including pupil-teacher ratio, pupil-classroom ratio, school size (measured by ACE enrolment), availability of digital devices, per capita spending, and the number of ACE centres. The outputs were determined by mean absolute scores in proficiency examinations and completion rates. Electricity and ACE graduates were linked to improved efficiency. Urban ACEs schools in ASALs region tend to exhibit greater technical efficiency compared to their rural counterparts. Some counties, despite being deemed efficient, do not necessarily achieve higher performance in test score results. The study recommends focusing on electricity, internet, digital literacy programs, and increased access to education for achieving the targets set in the sustainable development goals and constitutional framework by 2030.

Considerable investments have been directed towards Kenya's education sector, a testament to the nation's commitment to achieving the milestones outlined in Sustainable Development Goal 4. These efforts are also aligned with the vision set forth in the 2030 blueprint and in accordance with the commitments made in the Dakar framework for action back in 2000 to achieve Education for All (EFA). The assessment of efficiency in the education sector is important, not only for raising literacy levels but also for ensuring that the resources allocated to this sector are utilized in the most effective manner to attain the desired outcomes.

The findings of this study reveal that inefficiencies are prevalent across all categories of ACE Centres in Kenya, with an average technical efficiency of 78.8 percent. This suggests that there is room for improvement in learning outcomes for ACE Centres even with the existing level of input resources, potentially leading to a 21.2 percent enhancement. Interestingly, some counties, despite being deemed efficient, do not necessarily achieve commendable performance in test score results. Conversely, counties with comparable characteristics and inputs may yield markedly different outcomes. To gain deeper insights into these disparities, the study conducted further analysis employing a Tobit model. The results indicate that urban schools tend to exhibit greater technical efficiency compared to their rural counterparts. This highlights that the determinants of efficiency are contingent upon the geographical location of ACE Centres. Moreover, it was observed that ACE Centres of larger size tend to operate with higher efficiency levels than their smaller counterparts.

## 6.2 Policy Recommendations

Based on the preceding findings and conclusions, we propose a set of policy recommendations aimed at enhancing the efficiency and productivity of ACE Centres in Kenya without necessarily increasing inputs. It is important to implement policies that support effective management and operations within schools. This entails a continuous focus on upgrading the management skills of ACE Centre managers and Boards of Management through training initiatives. Additionally, establishing a mentorship system for school managers can provide valuable guidance and support. Ensuring teacher motivation is also critical in curriculum delivery. This can be achieved through improved terms of employment and the introduction of awards and recognition programs.

Furthermore, the study advocates for the implementation of policies that promote innovative and efficient utilization of existing teaching and learning facilities, without incurring additional costs. This may involve the adoption of Information and Communication Technology (ICT) in curriculum delivery, including the digitization of textbooks and the use of technology-based resources. These approaches can provide up-to-date materials to inform and support teaching and learning, while also allowing for flexible learning hours that enable learners to make optimal use of available resources.

Additionally, the study recommends the consolidation of small ACE Centres within the same locality and the pooling of resources. This stems from the observation that larger schools tend to operate with higher efficiency levels. Therefore, deliberate efforts be made to establish and ensure schools are optimally sized, allowing them to benefit from economies of scale. To fulfil the fundamental goal of providing every child with their basic right to access education, policies be implemented to balance the distribution of teaching and learning materials across all regions. This ensures effective utilization and equity. Consequently, both the national government and county authorities take steps to guarantee that all ACE Centres have sufficient infrastructure and teaching materials to compete favourably. Regular and vigilant monitoring of efficiency changes is essential to continually enhance the desired educational outcomes.

The policy recommendations include:

i) Enhance Access to Electricity: Provision of reliable and accessible electricity in all ASAL regions, particularly in areas with lower ACE center spending efficiency. This will facilitate the effective use of technology in learning

ii) Expand Internet Coverage and Digital Literacy Programs: Increase efforts to extend internet coverage and promote digital literacy programs. This will enable ACE centers to leverage technology for enhanced learning experiences

iii) Promote Enrolment in ACE Centers: This could be achieved through awareness campaigns, targeted outreach efforts, and policies that remove barriers to access. The strategy may include simplifying admission into ACE centres. The ACE centres will leverage on the economies of scale to improve spending efficiency.

iv) Promoting Economies of Scale: The positive relationship between ACE size (gross enrolment) and efficiency suggests that larger schools tend to operate more efficiently. Policymakers including ministry of education and directorate of Adult and Continuing Education may consider strategies to encourage the consolidation of smaller schools within the same locality, where feasible, to achieve economies of scale.

v) Location-Based Policies: Urban schools demonstrated higher levels of efficiency, Policymakers may consider policies that address the unique challenges faced by rural schools, such as improving access to resources and amenities.

vi) Investment in Digital Infrastructure- Given the significant impact of internet access and digital literacy programs on ACE school efficiency, policymakers may prioritize investments in digital infrastructure. This includes improving internet connectivity and providing adequate training in digital skills to both learners and educators.

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ISBN 978 9914 738 36 0

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