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Research Article

Cross-Efficiency Assessment of Primary Health Care in Benue State, Nigeria, using Data Envelopment Analysis

Friday Oduh Adejoh[1*] https://orcid.org/0000-0001-9027-3501 Emmanuel E Okoko [2] Innocent Dick[3] Mathias Abah Obute 4

[1,2,3]Department of Mathematics/Statistics, Benue State Polytechnic, Ugbokolo.
[4]Department of Computer Science, Benue State Polytechnic, Ugbokolo

Corresponding Author Email: afridayadejoh@gmail.com

Abstract- Health is the most important component of life. The entire globe strives for health outcomes that are effective, efficient, high-quality, and equitable, to enhance economic growth. The goal of this paper is to assess the performance of the primary healthcare (PHC) centres in order to effectively distinguish good performers in Benue State, Nigeria. Data collection was from 15 primary healthcare centres (PHCs) through the primary and secondary methods. Two input variables (number of beds and medical and non-medical staff) and 3 output variables (outpatients, inpatients, antenatal, deliveries, and quality of care) data obtained from the Benue State Primary Healthcare Board and the various PHCs form the variables and the sources of our data. The pair evaluation model and the Maverick index models were adopted. To evaluate the Data Envelopment Analysis (DEA) linear programming formulation, an R program was coded. The result of the aggressive and benevolent pair evaluation ranges between 0.2522 to 0.9335, and 0.2944 to 1.0000, respectively. Okpaflo and Ojapo PHCs are fully efficient and are the top performers in the aggressive and benevolent models, respectively. The Maverick index aided in detecting false efficiency. It is recommended that Policymakers, the Primary Healthcare Board, must accord a high level of importance to a rigorous form of PHC system performance evaluation. There is a clear need to build monitoring of efficiency into the information systems of each state's PHCs. Future research will be required in the private and mission hospitals that are nonhomogeneous.

Article Key Information

Keywords: Peer evaluation, Data envelopment analysis, Efficiency, Maverick, Primary healthcare

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1.0 Introduction

The absence of a fully developed and functional primary health care system continues to constitute a development challenge in Nigeria. The situation threatens the achievement of health-related sustainable Development Goals (SDGs) as well as other health objectives. One of the major challenges facing the health sector in Nigeria is the weakness of the country's primary health care system. Unfortunately, system weaknesses and long-term neglect have made ideal primary health care impossible to achieve. It is crucial to know the productivity of the PHCs and their advancement in the areas of efficiency and technology [1][2].

Inefficient use of health resources frequently results in a reduction of resources available to address other emergent health demands that could increase community well-being. It is critical that Nigeria evaluates its health care system, specifically the primary health care system, preferably among peers, and allocates available resources efficiently. This assessment is unquestionably important when it comes to making decisions about how to run healthcare systems better in different places [3][4].

Nigeria does poorly on a number of UHC metrics, including government spending on health (which is among the lowest in the region) and the proportion of health expenditure accounted for by out-of-pocket expenses (which is among the highest in the region). As a result, health results are substandard. For example, life expectancy has increased at a slower rate than in other African countries [5]. PHC must be revitalised and placed at the centre of efforts to promote health and well-being for three reasons: PHC characteristics allow the health system to adapt and respond to an ever-changing and complicated world. With an emphasis on promotion and prevention, addressing determinants, and a people-centred approach, PHC has been shown to be a highly effective and efficient way to address the primary causes and risk factors for poor health, as well as emerging challenges that may threaten health in the future. The World Health Organization and the UHC goals, as well as the health-related Sustainable Development Goals can only be achieved sustainably with a stronger emphasis on PHC [6].

Primary health care is critical for achieving the Sustainable Development Goals (SDGs) relating to health, which are intimately linked to the other SDGs such as poverty eradication, inclusive education, work and economic growth, inequality reduction, and climate action [1].
This paper aims to measure technical efficiency of PHCs using CCR DEA, apply aggressive & benevolent cross-efficiency evaluations and compute Mavericks indices, and to compare ranking orders and draw policy conclusion.
The remaining work is scheduled as follows: The second section examines related literature, the definition of CCR DEA, their advantages and limitations. Section three covers the materials and methods utilized in the study, identifies the variables, and describes the methodology for data collecting and analysis, model formulation, and r-code design. Section four presents the results obtained using the method above and subsequent discussion of the results. The fifth section concludes the study and outline some useful recommendations.

2.0 Review of Related Literature

Efficiency is defined simply (technically) as the ratio of the weighted sum of outputs to the weighted sum of inputs. Each decision making unit (DMU) is evaluated using a self-evaluation technique in which the weights are calculated in such a way that their efficiency relative to the other DMUs is maximised [7]. On the other hand, [8] proposed the concept of cross-efficiency as a peer-reviewed review that calculates each DMU's efficiency using the weights provided by the other DMUs for inputs and outputs. This technique enables improved discrimination of DMUs without imposing additional constraints [9][10], as well as classification of DMUs into good and poor performers. The cross-efficiency of the game ensures that the rating is unique and that it is acknowledged by all DMUs. This method has never been used in healthcare and hence represents an unfilled need.

In the majority of healthcare research, the efficiency of the health system is determined by the inputs (expenditure, hospital beds, and medical staff) used to produce outputs. Nonetheless, numerous issues have arisen on the output side of previous research as a result of their failure to address appropriate healthcare quality indicators [11]. Numerous healthcare outcome metrics, in particular, are not attributable to health system interventions but rather are influenced by a variety of factors external to the health system [12]. The health sector's primary objective is to deliver high-quality, safe services that meet the demands of patients. Improved service quality can result in increased adherence to medical treatment and more efficient use of health care [13]. Understanding the elements that influence users' views of the quality and safety of healthcare may lay the groundwork for developing effective policies aimed at increasing access to and the quality of health services [14].

Data envelopment analysis (DEA) is a mathematical model that uses linear programming to measure the efficiency of a number of decision-making units such as production units, banks or hospitals, by determining the optimal mix of its inputs (hospital resources) and its output (hospital services) based on actual performance. It aims to identify efficiencies and inefficiencies in the use of resources available to these institutions, and the most appropriate allocation of these resources by assessing the quality of their inputs and outputs [15].

The Charnes, Cooper, and Rhodes data envelopment analysis (CCR DEA) [16] examines efficiency values primarily through self-evaluation of decision-making units, and many effective decision-making units can be obtained that cannot be further rated [17]. [8] modified this method and introduced the concept of DEA cross efficiency. This method evaluates the relative efficiency of decision-making units by combining the outcomes of "self-assessment" and "other evaluation."

The cross-efficiency assessment technique assesses the overall efficiency of decision-making units (DMUs) by self- and peer-evaluation and can typically provide a complete ranking for the DMUs being reviewed. So, it makes DEA models more able to tell right from wrong and makes their weights more realistic [18]. The cross-efficiency assessment approach is a DEA extension that may be used to find high-performing DMUs and rank them.

The CCR DEA model doesn't always come up with the same set of optimal weights, so it's not easy to figure out how efficient a CCR DEA or cross-efficiency model is. Although DEA Cross-Efficiency has been applied in a variety of areas and has significantly enhanced performance, no application to the health care industry has been made. It is crucial to investigate the gap in this area.

DEA methods have been widely implemented in assessing the performance and production pattern of public and commercial hospitals in Nigeria's Oyo state [19], assess technical efficiency of the nine south Africa provinces [20], assess the efficiency of Health care facilities in sub-Saharan Africa [21].

All of the CCR DEA models presented before rely on a self-appraisal scheme, which can evaluate DMUs as DEA-efficient and cannot make any further distinction among them. The model cannot discriminate among DMUs that are deemed efficient [22]. In other words, a significant proportion of DMUs are viewed as effective performers while being otherwise dissimilar. By combining self- and peer-evaluation, Sexton et al. (1986) introduced the idea of DEA cross-efficiency to increase the discriminatory power of DEA among efficient DMUs. A cross-efficiency evaluation's primary objective is to ascertain the overall efficiency of DMUs via self- and peer assessments; it typically results in a comprehensive score for the DMUs under consideration [18]. It can, also, generate a unique ranking order for DMUs in the majority of realistic situations [23].

Falagario et al.,[24] Used to pick the best suppliers in public procurement tenders. The DEA cross-efficiency evaluation approach is used to evaluate suppliers with several performance indicators. Following that, the best provider is chosen. Similar applications are evident in the selection of advanced manufacturing technologies [22][25]. Lim et al., [26] applied DEA Cross-efficiency in Portfolio Selection in the Korean Stock Market That is, the strategy will usually pick a portfolio of funds (DMUs) that aren't very likely to change their weight when the value of their stock's changes. Ruiz & Sirvent, [27] used it in ranking decision-making units. Abolghasem et al., [28] applied DEA cross-efficiency to evaluate and compare long-run and short-run efficiency measures on an average basis. Carrillo, 2019 employed it to Measuring and ranking R & D performance at country level while Balk et al., [29] applied it in the evaluation of warehouse performance.

In summarry, ffirstly, the Nigerian primary healthcare is weak in terms of access, coverage and quality, infrastructure, administration, essential supplies and funding. The primary healthcare centres are inefficient. Most of the literatures uses 'qualitative and analysis of literature' method to assess PHC efficiency compared to the robust technology in the developed world. Secondly, no genuine research using DEA, the few existing ones only capture the elementary DEA that only stop at the efficient or inefficient stage.

3.0 Materials and methods

The materials and methods used will be looked at here.

3.1 Studied Areas and materials

This study focuses on the growth of primary health-producing activities in Benue's primary health care institutions. The quantitative cross-sectional survey method and inputs and outputs derived from earlier primary care efficiency measurement research were utilized [18][30].

3.2 Research design

Multiple-choice questionnaires are used to evaluate the opinions of the general public and the standard of care. This method was adapted to fit practical representations and create a large sample size in a short time. As a result, the respondents' views were taken as reflective of all PHC patients' responses. Each question was constructed using a 5-point Likert scale to ensure its validity, which allowed respondents to voice their opinions on the questions' directions.

3.3 Data source and collection

The data used come from the Primary health care board and Primary health care centres as well as administration of questionnaire. The analysis uses data for the years 2020, 2021 and 2022. The following 15 primary health care centres from Benue state were the source of data; Otukpo Town PHC, Adim health clinic, Ichama LG Health centre, Onipi PHC, Ugbokolo LG Health centre, Owukpa PHC, Adum Aiona Com Health centre, Ogege PHC, Okpaflo PHC, Adoka PHC, Ojapo LG health centre, Adiga LG Health centre, Orokam PHC, Ogodumu PHC, Opialu LG PHC, Aho-Ogbo Com. Health care. The primary and secondary data collection method was adopted here. The choice of the 15 PHCs was based on the availability of data. The choice of sample size is to ensure that the relative efficiency scores are not compromised by the problem of degree of freedom. In DEA, the number of degrees of freedom increases as the number of DMUs increase and vice-versa [31].

To determine the quality of care, a questionnaire was administered to 20 patients in each of the PHCs chosen, and we used Excel to calculate the proportion of affirmative responses indicating good quality, and the value was used to estimate the quality of care for that PHC.

There is no best practice method regarding the choice of input and output variables that should be used in efficiency measurement. The implications of using one variable rather than another can indeed be compared; however, there are many variables that can be used to measure input and output [32].

The selection of the most appropriate health or health care production input and output variables is one of the most critical and difficult aspects of conducting a technical efficiency study using DEA methodology [31]. Human resources are also essential and basic components of health production technology [31]. The choice of input and output variables was constrained by the absence of PHC expenditure per capita data in Nigeria. Thus, researchers lack statistics on inputs measured in terms of money. In other words, they are directly controlled by health policymakers and development planners.

3.4 Reliability and validity

Twenty participants outside our study area were initial administered questionnaire, and SPSS 24 was used to analysed the data. Using Cronbach's alpha value test for issue consistency, a reliability test was constructed for 28 survey questions using a 5-point Likert scale; the outcome was 0.932, which is above the minimum threshold of 0.70. The responses indicated that the structure of the question is internally consistent. Face and Content Guidelines were used to establish credibility.

3.5 Study Population and sampling

All primary health care facilities, or decision-making units in Benue state, comprised the population. For the actual survey, a sample size of 20 respondents per PHC was chosen. The inputs and outputs were chosen based on prior primary care efficiency appraisals and included all primary care center producing inputs and outputs, in addition to healthcare professional tasks and service categories [32]. Depending on the number of input and output variables, Recai and Bahce [33] state that the minimum number of DMUs necessary for sound DEA applications on efficiency analysis should be at least (n * m) or at least 2 (n + m). In addition, they recommend at least 3 (n + m) DMUs and at least 2 (n * m) DMUs.

Previous empirical studies have shown that physical inputs such as labour (number of staff members, physicians, nurses, mix of medical staff, specialists, and other administrative staff), capital (number of beds, health facility space, total cost of capital, value of equipment), and financial inputs (expenses for staff, drugs and medical supplies, price of office space) have become the dominant inputs in health care [34][35][36][37][38][39][40][41][42][43] .

Hospital beds: The number of hospital beds shows how many services can be given to people who are staying in the hospital. Beds can be viewed as a representation of the variation in service technology as well as an approximation of the capital and technological input of various hospitals [44][45][40]. Total number of inpatient beds available in PHC facility is used in this study.

Medical and non-medical staff: Frequently, labour input is disaggregated by skill level in hospital efficiency studies [44][20]. Since the majority of data is accessible in head count units, head counts are used to measure hospital employment rather than full-time equivalents. The total number of medical and non-medical staff employee in each PHC centre is used as the data.

A typical production system like health system utilised input resources in the conversion process to produce a set of outputs that are demanded by consumers. PHCs' being a productive entity utilizes different inputs to produce or provide a range of consumer- satisfying patients. Thus, in primary health care efficiency studies, their output is measured as an array of health services provided. These services can be based on direct observation of the patient and/or providing bed-side treatment. These can be categorized as inpatient, outpatient and emergency services.

Output variables can be the quantity of health services rendered or a combination of the quantity and quality of the health care services. The health service outputs quantity mostly used by studies are outpatients, inpatients, antenatal care (maternal and child health services), delivery, immunization, postnatal, and family planning visits. Health service quality or health outcomes were measured through considering records of average facility service quality index score, domiciliary cases treated, new births discharged alive, and inpatients discharged alive [32][21].

Health service measures are used as output variables in most literature. The most common health service items in hospitals were 1) the number of outpatient visits, 2) inpatient days. The typical outputs used in primary care settings were outpatient visits and other services including the number of fully immunized children, the number of individuals enrolled in nutrition services, and the number of prescriptions. In some studies, the outputs were categorized by the type of services (e.g. family planning, child health services) and by condition (e.g. typhoid, malnutrition).

Output data focuses on the quantity of health care process production, such as services rendered or patients treated [45]. Outputs utilized in this study include outpatient, inpatient, antenatal, deliveries, and care quality. Other health service outputs used in literature include immunization, postnatal, family planning, service quality index score, domiciliary cases treated [21]. These variables are left out due to unavailability of data.

Inpatients: The number of inpatients who depart a PHC after receiving care. The annual total number of inpatients per year are taken as data for the inpatient variable.

Outpatients: outpatients services refer to all medical and paramedical services delivered to patients attending outpatient facilities and are not formally admitted to the hospital. Patients consult with medical personnel in private or as outpatients. Outpatient data consists of yearly records of outpatients.

Antenatal: Number of pregnant women attended to at the PHC Centre. Women with three complete antenatal check-ups yearly are used as data here.

Deliveries: Number of child deliveries. PHC resources are expended on deliveries, thus our definition includes all deliveries in each facility.

Quality of care: Quality of care is a valued and desired outcome of health system performance that helps to increase the effectiveness of service delivery. Respondents' assessment of the healthcare quality in their country using one of the answer categories: very good/fairly good/fairly bad/very bad. Percentage of answers reporting good quality form the units.

3.6 Ethical Consideration

The Executive Secretary of the Benue State Primary Healthcare Board approved the study of the research. The participant was informed of the aims and benefits. Each participant signed or thumb-printed a consent form and was assured of the strictest confidentiality prior to receiving a copy of the questionnaire. Consent was obtained for the study findings to be published for public consumption. Participants were permitted to answer questions voluntarily and to opt out.

3.7 Data analysis method

This study uses three models in order to achieve its objectives. There are: the standard DEA model, the DEA peer Aggressive and Benevolent model, and the Maverick index.

An input-oriented approach is proposed. This is because the emphasis is placed on optimising the use of available health input resources to provide the greatest possible health care output. This approach is appropriate for PHCs since the department of health and the Primary Health Care Board (PHCB) have greater control over the inputs than the outputs of the health system. This agrees with the viewpoint of [46]. The input-oriented model is accepted on the grounds that, according to [47], who conducted a comparative analysis of the output-oriented (BCC model) and the input-oriented (CCR model), the input-oriented model is applicable in the following situations:

i. DMUs should be homogeneous, meaning they should be a part of the same organization without significant differences in size.
ii. The fundamental DEA method based on the CCR model is applied to the unitary evaluation of homogenous units (rather than organizations). The CCR can be employed only when the criteria of homogeneity are met by the units or branches of the same business unit.
iii. The component pure technical efficiency (PTE) and the scale efficiency make up the overall technical efficiency (OTE) (SE). Therefore, when the scales differ, CCR should not be applied.
iv. The CCR model implies ideal competition, which is demonstrably not the case in actuality. DMUs may not operate at their optimal size due to imperfect competition, financial limitations, control measures, and other issues.

To use the basic CCR model, it is important to look at DMUs to see if they don't have any of the above-mentioned variables.

3.7.1 Model 1: The Standard DEA

DEA is a non-parametric method for calculating the efficiency of an array of homogeneous decision units in a production line with a large number of inputs and outputs [48]. Charnes et al. [16] characterized the input-oriented constant return to scale (CRS) of the standard CCR model as follows:

$$\boldsymbol{E_{kk} = max\,\theta = \sum_{r=1}^{s} u_r y_{rk}}$$

$$\textbf{s.t} \quad \boldsymbol{\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \; j = 1, \dots, n} \qquad \textbf{(1)}$$

$$\boldsymbol{\sum_{i=1}^{m} v_i x_{ik} = 1}$$

$$\boldsymbol{v_i \geq 0, \; i = 1, 2, \dots, m; \qquad u_r \geq 0, r = 1, 2, \dots, s}$$

When PHC_k is the unit being evaluated, the variables u_r and v_i represent the multipliers (weights) of outputs r and inputs I accordingly. If PHC k's simple efficiency is one, it is efficient; else, it is inefficient. When the given model is solved, the input-oriented (self-evaluated) performance value PHC k is obtained. It is stated as:

$$\mathbf{E_{kk}} = \frac{\sum_{r=1}^{s} u_r^* y_{rk}}{\sum_{i=1}^{m} v_i^* x_{ik}}$$

Where u_r^* and v_i^* are the optimal weight values selected by PHC k in (1)

3.7.2 Model 2: Cross-efficiency model

Cross-efficiency models use self-and peer-evaluations to assess the total efficiencies of decision-making process units, in this case, PHCs, and can often generate an all-encompassing value for the PHCs under examination. The approach enhances the discrimination ability and accuracy of DEA models' weights [18].
If the most acceptable weights are used to evaluate the other PHCs using a peer-evaluation method [48], the following input-oriented cross-efficiency ratings are produced:

$$\mathbf{E_{jk}} = \frac{\sum_{r=1}^{s} u_r^* y_{rk}}{\sum_{i=1}^{m} v_i^* x_{ik}}$$

This methodology evaluates the performance of PHC j via the perspective of PHC k. The Average Cross-Efficiency (ACE) score is determined by aggregating the self- and peer-ratings of each PHC's efficiency. This score gives a comprehensive evaluation of the Jth DMU and considers the input and output parameter choices of all DMUs [48]:

$$\mathbf{ACE_j} = \frac{1}{n}\sum_{k=1}^{n} \mathbf{E_{jk}}$$

The ACE j index is an empirical measure of the average cross-efficiency of primary health care centres (PHCs), which has been shown to be effective in discriminating between good and bad PHCs. Doyle and Green [49] presented aggressive and benevolent secondary formulations. The benevolent objective of cross efficiency is to maximize the efficiency of each PHC, while the aggressive aim is to minimize the cross-efficiencies. The aggressive formulation improves the value discrimination efficiency. The two models are given as follows:

Aggressive formulations

$$\min_{u,v} \sum_{i}^{outputs} u_{ik} \sum_{s\neq k} y_{is} - \sum_{j}^{inputs} v_{jk} \sum_{s\neq k} x_{js}$$

Subject to;

$$\sum_{j}^{inputs} v_{jk}\, x_{jk} = 1$$

$$\sum_{i}^{outputs} u_{ik}\, y_{ik} - E_{kk} \sum_{j}^{inputs} v_{jk}\, x_{jk} = 0$$

$$\sum_{i}^{outputs} u_{ik}\, y_{ik} - \sum_{j}^{inputs} v_{jk}\, x_{jk} \leq 0, \forall s \neq k$$

$$u_{ik}, v_{ik} \geq 0$$

Benevolent formulations

$$\max_{u,v} \sum_{i}^{outputs} u_{ik} \sum_{s\neq k} y_{is} - \sum_{j}^{inputs} v_{jk} \sum_{s\neq k} x_{js}$$

Subject to; $\sum_{j}^{inputs} v_{jk}\, x_{jk} = 1$

$$\sum_{i}^{outputs} u_{ik}\, y_{ik} - E_{kk} \sum_{j}^{inputs} v_{jk}\, x_{jk} = 0$$

$$\sum_{i}^{outputs} u_{ik}\, y_{ik} - \sum_{j}^{inputs} v_{jk}\, x_{jk} \leq 0, \forall s \neq k$$

$$u_{ik}, v_{ik} \geq 0$$

The value for PHC k's efficiency is the average of the kth column of the cross-efficiency matrix, ignoring self-efficiency.

3.7.3 Model 3: Maverick index.

A PHC can attain optimum efficiency by assigning extremely high weights to some parameters and extremely low weights to others. This can lead to an undesirable error in ranking PHCs. This circumstance pertains to Maverick. The Mavericks have a decreased chance of receiving a passing score on a test measuring cross-efficiency. They can aid in detecting an incorrect estimate. Effective in limiting the choice of mavericks within a PHC, the DEA cross-efficiency assessment is expected to choose only PHCs with at least reasonable performance across all metrics and exclude DMUs with excellent performance on only a subset of measurements [50][51]. Doyle and Green [9] designed the maverick index to distinguish DMUs with unusual weights. The index represents the difference between a measure's self-efficiency and cross-efficiency scores [51].
Maverick is the difference between the self-efficiency ($\mathbf{E_k}$) and cross-efficiency ($\mathbf{e_k}$) scores for a DMU K [52]. A significant $\mathbf{M_k}$ value indicates that the weighting method is unworkable. Mavericks are DMUs having a M K greater than 20%. A false positive is a PHC with a self-efficiency of 1 but a high $\mathbf{M_k}$. The cross-efficiency scores can be used to measure the degree to which PHCs' peer- and self-appraisal efficiency varies. The "Maverick" index quantifies the congruence of the two efficiencies and is defined as

$$\mathbf{M_k} = \frac{(\mathbf{E_k} - \mathbf{e_k})}{\mathbf{e_k}}$$

Where $\mathbf{E_k}$ denotes the average peer-appraisal efficiency of PHC k, and $\mathbf{e_k}$ denotes the DEA's simple efficiency or self- appraisal efficiency of PHC k [53][54].
The higher the M_k value, the more unconventional (maverick) the assessed DMU k is [55]
An R computer code for continuous return to scale DEA and cross-efficiency was developed in order to estimate the values for efficiency, cross-efficiency matrices, and aggressive and benevolent cross-efficiency.

Model formulation

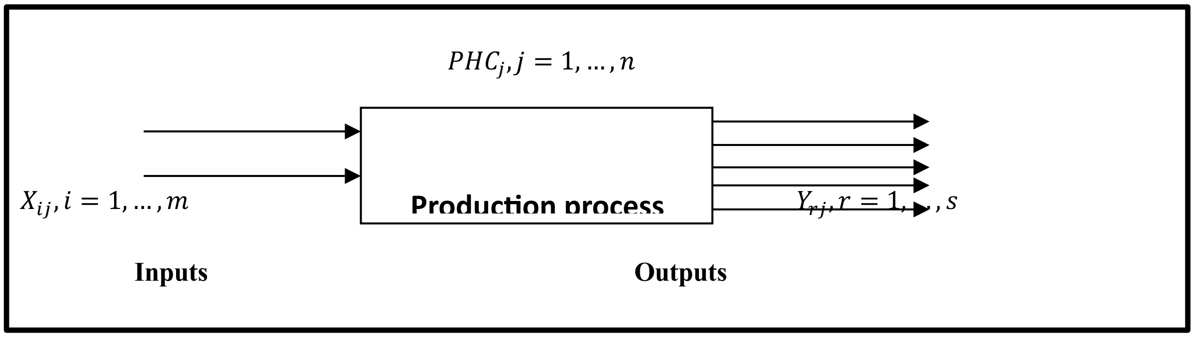

Figure1**:** Model of production process of primary health care

Consider n PHCs, where each PHC_j $(j = 1, \dots, n)$ uses m inputs $X_{ij} = (x_{1j}, x_{2j}, \dots, x_{mj}) > 0$ to generate s outputs $Y_{rj} = (y_{1j}, y_{2j}, \dots, y_{rj}) > 0$. The optimal variable weights are u_r for outputs and v_i for inputs. y_{ro} and x_{io} are the input and output values for the evaluated PHC_j. Any PHC's efficiency is determined by the highest ratio of overall weighted outputs to whole weighted inputs, with the restriction that similar ratios for all PHCs are less than or equal to one (see Figure 1).

The following is the mathematical expression:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_r y_{rj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots v_i x_{ij}}$$

Where u_1 = weights assign to output 1, y_{1j} = the amount of output 1 from unit j,

v_1 = weights given to input 1, and x_{1j} = the amount of input 1 unit j.

The linear programming formulation of the model is given as;

$$\mathbf{max\theta = u_1 y_{1j} + u_2 y_{2j} + u_3 y_{3j} + u_4 y_{4j} + u_5 y_{5j}}$$

Subject to;

$$\mathbf{v_1 x_{1j} + v_2 x_{2j} = 1}$$

$$\mathbf{u_1 y_{1j} + u_2 y_{2j} + u_3 y_{3j} + u_4 y_{4j} + u_5 y_{5j} \leq v_1 x_{1j} + v_2 x_{2j}}$$

$$\mathbf{u_r \geq 0, r = 1, 2, 3, 4, 5}$$

$$\mathbf{v_i \geq 0, i = 1, 2}$$

The linear programming formulation utilizing our survey data for Otukpo PHC is giving below. Similarly, we develop linear programming for the remaining 14 PHCs.

Primary Health care**: Otukpo.**	
Objective function	$max\theta = 2066u_1 + 329u_2 + 1122u_3 + 237u_4 + 95u_5$
Subject to the following constrains;	$15v_1 + 23v_2 = 1$
$Adim\ PHC$	$815u_1 + 38u_2 + 161u_3 + 15u_4 + 85u_5 - 8v_1 - 7v_2 \leq 0$
$Ichama\ PHC$	$934u_1 + 29u_2 + 233u_3 + 28u_4 + 80u_5 - 12v_1 - 11v_2 \leq 0$
$Onipi\ PHC$	$502u_1 + 36u_2 + 223u_3 + 30u_4 + 75u_5 - 7v_1 - 6v_2 \leq 0$
$Ugbokolo\ PHC$	$1117u_1 + 247u_2 + 157u_3 + 104u_4 + 95u_5 - 19v_1 - 14v_2 \leq 0$
$Owukpa\ PHC$	$294u_1 + 28u_2 + 82u_3 + 22u_4 + 85u_5 - 10v_1 - 10v_2 \leq 0$
$Adum - aiona\ \ PHC$	$210u_1 + 40u_2 + 29u_3 + 10u_4 + 90u_5 - 8v_1 - 6v_2 \leq 0$
$Ogege\ PHC$	$479u_1 + 90u_2 + 82u_3 + 5u_4 + 75u_5 - 6v_1 - 4v_2 \leq 0$
$Okpaflo\ PHC$	$207u_1 + 88u_2 + 234u_3 + 78u_4 + 80u_5 - 4v_1 - 4v_2 \leq 0$
$Ojapo\ PHC$	$972u_1 + 108u_2 + 292u_3 + 6u_4 + 85u_5 - 4v_1 - 5v_2 \leq 0$
$Adiga\ PHC$	$386u_1 + 39u_2 + 65u_3 + 14u_4 + 80u_5 - 5v_1 - 7v_2 \leq 0$
$Orokam\ PHC$	$597u_1 + 4u_2 + 208u_3 + 17u_4 + 90u_5 - 11v_1 - 12v_2 \leq 0$
$Ogodumu\ PHC$	$1087u_1 + 6u_2 + 378u_3 + 60u_4 + 70u_5 - 5v_1 - 4v_2 \leq 0$
$Opialu\ PHC$	$482u_1 + 51u_2 + 108u_3 + 81u_4 + 80u_5 - 7v_1 - 8v_2 \leq 0$
$Aho - Ogbo\ PHC$	$60u_1 + 11u_2 + 14u_3 + 8u_4 + 75u_5 - 3v_1 - 4v_2 \leq 0$

4.0 Results and Discussion

Table 1 presents the descriptive statistics for all inputs, intermediate variables, and outputs for the 15 PHCs in Benue State in 2022. On average, PHCs operated with 9 staff and 9 beds, indicating obvious under-resourcing relative to the national minimum standards for primary health care in Nigeria [56]. The low variability across input resources also indicates that PHCs have not experienced meaningful growth in resource allocation over the years. This finding aligns with widespread reports of chronic underfunding and infrastructure stagnation in Nigerian PHCs, which previous studies [57]–[60] have identified as major contributors to inefficiency and poor utilization.

The average number of inpatients treated was 86, while outpatient consultations averaged 715 in 2022. The persistently low output levels may be attributed to several factors, including limited accessibility, a lack of essential equipment, irregular facility opening hours, and provider competence issues. The average delivery rate was 38, while antenatal care attendance averaged 287. Although antenatal visits appear to increase slightly, the values remain too small to be of practical significance. These output gaps reinforce earlier findings that PHCs with low staffing and inadequate equipment struggle to attract and retain clients, thereby perpetuating low service utilization [57–60].

Furthermore, the unfavourable staff-to-patient ratios, particularly in outpatient and inpatient care, align with the views of [57]–[60] concerning the drivers of poor PHC utilization in Nigeria. These ratios highlight operational inefficiencies, suggesting that even available staff are overburdened, reducing the probability of achieving optimal service coverage.

Table 1. Descriptive Statistics for Input and Output Variables (n = 15, Benue State PHCs, 2022)

Statistic	Beds	Medical/Non-medical Staff	Outpatients	Inpatients	Antenatal	Delivery	Quality of Care
Mean	8.27	8.33	541.27	85.13	227.67	45.13	82.67
SD	4.46	5.15	698.12	138.71	315.12	72.87	7.73
Min	3	4	90	1	7	2	70
Max	19	23	2854	537	1231	283	95

There was no indication of multicollinearity among variables, as all correlation coefficients were below the 0.90 threshold. This validates the suitability of the selected input–output variables for DEA modelling, ensuring that the efficiency scores are not distorted by redundant relationships.

All DEA models were implemented using custom R scripts for CCR efficiency and cross-efficiency computation. The reliance on R scripts enhances reproducibility and aligns with methodological best practices in non-parametric efficiency analysis.

Tables 2 and 3 present the aggressive and benevolent cross-efficiency matrices. Both matrices reveal varying efficiency interactions among PHCs.

Table 2. Aggressive Cross-Efficiency Matrix (15 PHCs)

Panel A: PHCs 1–5

PHC	Otukpo	Adim	Ichama	Onipi	Ugbokolo
Otukpo	1.0000	0.0133	0.1502	0.1893	0.3403
Adim	0.2065	0.6071	0.3636	0.6250	0.3393
Ichama	0.7032	0.0536	0.5040	0.4831	0.2332
Onipi	1.0000	0.2455	0.4198	0.7947	0.7176
Ugbokolo	0.2720	0.0261	0.1043	0.1695	1.0000

Panel B: PHCs 6–10

PHC	Owukpa	Adum-aiona	Ogege	Okpaflo	Ojapo
Owukpa	0.4250	0.7500	0.9375	1.0000	0.8500
Adum-aiona	0.4250	0.7500	0.9375	1.0000	0.8500
Ogege	0.3190	0.6093	1.0000	0.9841	1.0000
Okpaflo	0.0292	0.0131	0.1236	1.0000	0.9011
Ojapo	0.0259	0.0087	0.0732	0.8878	1.0000

Panel C: PHCs 11–15

PHC	Adiga	Orokam	Ogodumu	Opialu	Aho-ogbo
Adiga	0.7263	0.3674	0.6443	0.5259	1.0000
Orokam	0.6421	0.4056	0.9333	0.5018	0.9146
Ogodumu	0.6421	0.4056	0.9333	0.5018	0.9146
Opialu	0.7263	0.3674	0.6443	0.5259	1.0000
Aho-ogbo	0.6400	0.3273	0.5600	0.4571	1.0000

Table 3. Benevolent Cross-Efficiency Matrix (15 PHCs).

Panel A: PHCs 1–5

PHC	Otukpo	Adim	Ichama	Onipi	Ugbokolo
Otukpo	1.0000	0.2455	0.4198	0.7947	0.7176
Adim	0.2065	0.6071	0.3636	0.6250	0.3393
Ichama	0.7032	0.0536	0.5040	0.4831	0.2332
Onipi	1.0000	0.2455	0.4198	0.7947	0.7176
Ugbokolo	1.0000	0.0494	0.1983	0.2810	1.0000

Panel B: PHCs 6–10

PHC	Owukpa	Adum-aiona	Ogege	Okpaflo	Ojapo
Owukpa	0.4250	0.6923	0.8333	1.0000	0.8947
Adum-aiona	0.4250	0.7500	0.9375	1.0000	0.8500
Ogege	0.3582	0.6593	1.0000	1.0000	1.0000
Okpaflo	1.0000	0.3016	0.6622	1.0000	1.0000
Ojapo	1.0000	0.3016	0.6622	1.0000	1.0000

Panel C: PHCs 11–15

PHC	Adiga	Orokam	Ogodumu	Opialu	Aho-ogbo
Adiga	1.0000	0.3674	0.6443	0.5259	1.0000
Orokam	0.6421	0.4056	0.9333	0.5018	0.9146
Ogodumu	0.6421	0.4056	0.9333	0.5018	0.9146
Opialu	0.7263	0.3674	0.6443	0.5259	1.0000
Aho-ogbo	0.6719	0.4034	0.8453	0.5209	1.0000

The aggressive and benevolent cross-efficiency values ranged between 0.2522–0.9335 and 0.2944–1.000, respectively (Table 4). Both approaches show similar variation patterns, though the benevolent model generally yields higher values. This is expected, as the benevolent model tends to favor peer-friendly scoring, while the aggressive model penalizes poor performers more strongly, thereby offering sharper discrimination.

Okpaflo and Ojapo ranked highest across all models, while Owukpa (aggressive) and Orokam (benevolent) ranked lowest, indicating critical performance gaps requiring policy attention. Their consistently low scores suggest structural inefficiencies, resource management issues, or severe deficits in service delivery capacity.

Although Ugbokolo was rated efficient under the CCR model, its lower ranking under both cross-efficiency models indicates hidden performance weaknesses. Conversely, Adiga improved from inefficient (CCR) to higher rankings in both cross-efficiency assessments. This reinforces the view that classical CCR models often mask underlying inconsistencies, while cross-efficiency provides clearer insight into true operational performance.

Table 4. CCR Efficiencies, Cross-Efficiencies, and Mavericks of PHCs

PHC	CCR Efficiency (Rank)	Aggressive Cross-Efficiency (Rank)	Maverick	Benevolent Cross-Efficiency (Rank)	Maverick
Otukpo	1.0000 (1)	0.5049 (7)	0.9806	0.6009 (7)	0.6641
Adim	0.6071 (11)	0.3404 (13)	0.7834	0.3974 (12)	0.5279
Ichama	0.5040 (13)	0.3461 (12)	0.4562	0.3780 (13)	0.3332
Onipi	0.7947 (8)	0.5137 (6)	0.5471	0.6402 (6)	0.2414
Ugbokolo	1.0000 (1)	0.4104 (9)	1.4364	0.5110 (9)	0.9569
Owukpa	0.4250 (14)	0.2522 (15)	0.6849	0.2944 (15)	0.4436
Adum-aiona	0.7500 (9)	0.4088 (10)	0.8346	0.4805 (10)	0.5609
Ogege	1.0000 (1)	0.5980 (5)	0.6721	0.7229 (4)	0.3834
Okpaflo	1.0000 (1)	0.9335 (1)	0.0712	1.0000 (1)	0.0000
Ojapo	1.0000 (1)	0.8788 (2)	0.1380	0.9730 (2)	0.0278
Adiga	0.7263 (10)	0.4537 (8)	0.6006	0.5610 (8)	0.2947
Orokam	0.4056 (15)	0.2844 (14)	0.4261	0.3353 (14)	0.2095
Ogodumu	0.9333 (7)	0.6176 (4)	0.5113	0.7524 (3)	0.2404
Opialu	0.5259 (12)	0.3652 (11)	0.4402	0.4372 (11)	0.2027
Aho-ogbo	1.0000 (1)	0.6183 (3)	0.6173	0.7163 (5)	0.3960

The aggressive model identified 13 Mavericks ($Mk > 0.20$) and four false-positive efficiencies (Otukpo, Ugbokolo, Ogege, Aho-ogbo). The benevolent model also identified 13 Mavericks. Only Okpaflo and Ojapo showed no Maverick tendencies across both models, marking them as genuinely efficient. This dual confirmation strengthens the reliability of their performance ratings and signals best-practice opportunities for peer learning across the PHC network.

Cross-efficiency methods, therefore, provide superior discrimination among PHCs compared to CCR DEA, especially in settings with many units tied at efficiency = 1. This supports findings by Chu [61] that heterogeneous health facilities require more robust ranking methodologies. The ability of cross-efficiency to reveal hidden inefficiencies makes it especially valuable for PHC systems characterized by inconsistent resource availability and variable service outputs.

Overall, DEA and cross-efficiency analysis provide strong diagnostic tools for identifying optimal resource allocation pathways. Efficient PHCs support progress toward universal health coverage (UHC) and SDG health targets by reducing pressure on secondary and tertiary facilities. This is critical in Benue State, where overdependence on higher-tier hospitals persists due to weak PHC performance.

However, allocative efficiency was excluded from this study due to the unavailability of reliable input price data. Future research should incorporate allocative efficiency to provide a more comprehensive performance evaluation. Such integration would offer policymakers stronger evidence for budget allocation and workforce optimization.

Figure 2 depicts the CCR DEA, aggressive, and benevolent cross-efficiency rating histograms. The chart compares the CCR DEA with the two cross-efficiency models.

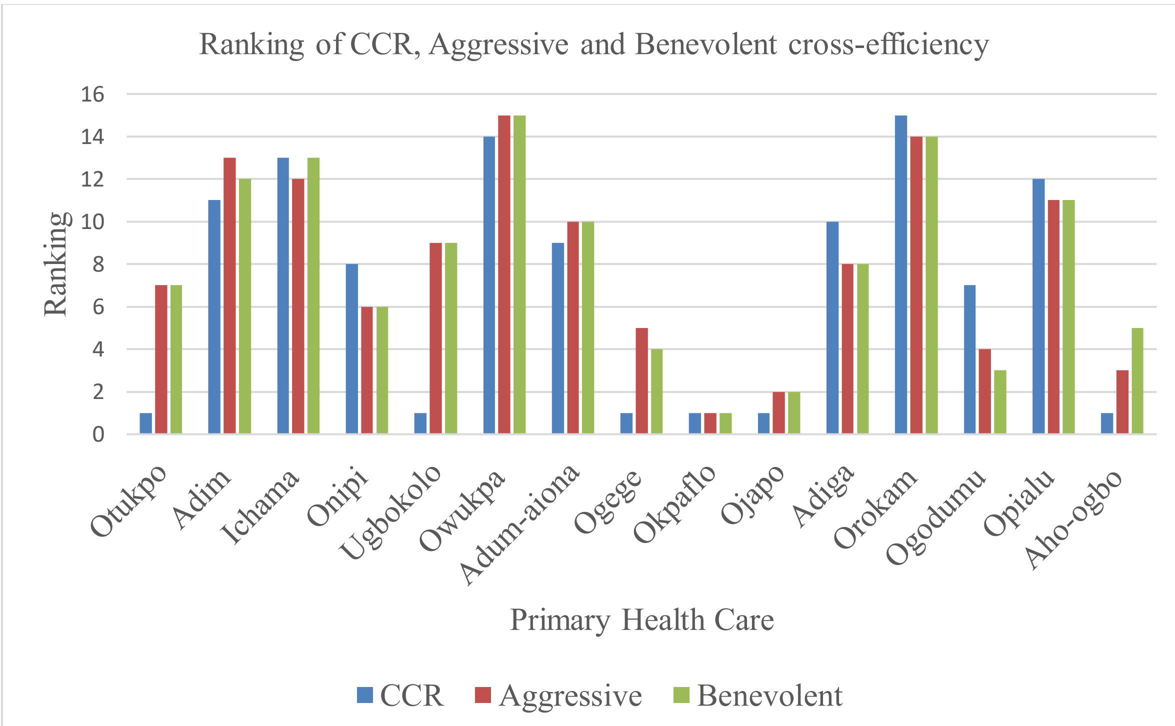

Figure 2: Ranking of CCR, Aggressive and Benevolent cross-efficiency

5.0 Conclusions and Recommendations

5.1 Conclusion

This research studies and evaluates the effectiveness of 15 PHCs in Benue State, Nigeria, considering the growing emphasis on primary health care centres. Using the CCR DEA model, we determine that 13 of the 15 PHCs are efficient. Because DEA does not allow for additional differentiation across efficient units, a cross-efficiency evaluation approach is applied to generate an overall score for comparing and ranking PHCs. Notably, numerous PHCs that performed well in the CCR model performed miserably in the aggressive and benevolent cross-efficiency models. However, several PHCs were efficient in the CCR model but not in cross-efficiency techniques; they are mavericks. Cross-efficiency has been able to evaluate the peer-efficiencies and establish the unique order of performance from the aggressive and benevolent ranking of the PHCs and the results also agree with that of Ibikunle

[19] that Nigeria's primary health care centres aren't very good because they lack basic infrastructure, people don't use them much, employees aren't motivated, there isn't enough monitoring, quality, and fairness, and they aren't run well.

5.2 Recommendations

This study's major purpose is to shed light on and fill knowledge gaps about the efficiency of primary care in the overall delivery of health services. Generally, efficiency studies are predicated on the concept that more output can be attained by intensive utilisation of the resources now available. The following suggestions have been made to help the National Primary Healthcare Board and the State Primary Healthcare Board do their jobs as watchdogs and improve the performance of PHCs in terms of efficiency.

The prevalence of inefficiency in the state's PHCs highlights the necessity for managerial interventions by the organisations responsible for their oversight. Such managerial actions could target the removal of health input resources from inefficient PHCs and the redistribution of the liberated resources to PHCs that are currently maximising their resources. Consequently, the input savings will assist in addressing the disparities in the primary healthcare system and extending care to a larger portion of the population.

It may be necessary to restructure the health system so that a specified number of primary healthcare facilities are associated with a general hospital that has an acceptable level of management control over the affiliated primary institutions. This will increase health care delivery at the primary level and the referral system in the national health system, maximising the use of resources at both care levels. By bridging the management gap between the primary facilities and the organ responsible for these facilities, this strategy has the advantage of reducing absentee control of the primary facilities.

Consider the alternative of "right-sizing" the PHCs in accordance with their output profile as a means of addressing the issue of scale inefficiency. PHCs in close proximity to one another could be integrated or synced. However, careful planning is required because this approach may present political and demographic obstacles. Population density must be taken into account, and the fact that hospitals are sometimes used as political leverage may generate resident and political opposition to merger choices.

Moreover, in light of the current performance of some of these PHCs, which qualifies them to serve as benchmarks or role models, it may be advantageous for management to consider conducting a comprehensive analysis of the PHCs' characteristics, operating environment, and other factors that appear to have contributed to their efficiency performance. An examination of the input profiles of peer groups relative to inefficient PHCs will highlight the areas requiring the most attention in terms of adjusting the health inputs of inefficient facilities.

Current economic conditions in a developing nation like Nigeria show that efficiency as a policy target may be more cost-effective. This is to decrease the moral and ethical burden on the government of increasing resource allocation to a sector whose administration of entrusted public resources has demonstrated inefficiency. If these kinds of legislative steps are taken in this way, it will give donors more confidence to send money to the PHC sector.

Policymakers, the Primary Healthcare Board must accord a high level of importance to a rigorous form of PHC system performance evaluation. There is a clear need to build monitoring of efficiency into the information systems of each state's PHCs.

This study demonstrates that policymakers, managers, and health professionals are ignorant of the notion of efficiency, which contributes to the current degree and pattern of operating inefficiency of primary health institutions. As a result, it may be necessary to foster linkages with academic institutions that can educate managers and policymakers on efficiency, as efficiency is the key to maximising the benefits from the resources invested in primary healthcare and enhancing the government's capacity to expand health services to a larger population.

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Data and materials accessibility
The research data is protected by strict confidentiality and can be provided on demand. The R code can be obtain on demand.

Author Contribution
Friday Oduh Adejoh: Data curation, Writing –review & editing, Formal analysis. **Okoko E.E** : Writing –review & editing. **Obute M.A:** R coding and analysis. **Dick I**: Investigation, Visualization.

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