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Exploring the Use of Data Envelopment Analysis for Formative Evaluation of Senior High Schools in Ghana

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Abstract

This study explores the use of data envelopment analysis (DEA) for the formative evaluation of senior high schools (SHS) in Ghana and investigates how the DEA results can help improve their performance. By assessing the relative performance of 215 public SHS across five regions (Greater Accra Region, Ashanti Region, Central Region, Upper West Region, and Upper East Region), the study contributes to the broader discourse on knowledge-based economies by demonstrating how data-driven insights can optimize resource allocation and improve human capital development. The schools are classified into groups A, B, and C based on students' entrance examination scores, and a hierarchical categorization DEA procedure is applied to assess them across three dimensions: resource efficiency, resource effectiveness, and effectiveness. This study highlights the crucial role of knowledge creation, diffusion, and application in education management by fostering deep engagement with decision-makers, ensuring the acceptance of DEA results, and promoting continuous improvement in institutional performance. The findings reveal significant disparities in school efficiency and effectiveness, underscoring the need for structured knowledge-sharing mechanisms. To support sustained performance improvement and better resource utilization, we propose the establishment of an educational performance observatory. This initiative would function as a platform for knowledge diffusion, enabling underperforming schools to benchmark against high-performing institutions, thus reinforcing the foundational role of knowledge exchange in strengthening educational systems and, by extension, the knowledge economy.

Keywords Data envelopment analysis · School performance assessment · Efficiency · Effectiveness · Knowledge-sharing

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Introduction

The demand for quality education and the measurement of school efficiency have been major concerns worldwide, as the improved socio-economic status of diverse social groups (Brown et al., 2013) and the overall economic growth of nations are strongly linked to the quality of education provided to their citizens (Hanushek & Woessmann 2010; 2012).

According to Heckman (2000), investment in education can contribute immensely to the development of human capital and have valuable outcomes for the wellbeing of a community. For emerging nations, such as those in Africa, where the social returns on education can be particularly large, investment in education as a pathway to prosperity is of utmost importance (Hanushek, 2013).

This demand for quality education by stakeholders has inevitably influenced decisions regarding the allocation of funds, investment in personnel, capital, and other resources for the education sector (Abreh, 2017). Currently, the proportion of Gross Domestic Product (GDP) and budgetary expenditure on education in Ghana is regarded as one of the highest within the Economic Community of West African States (ECOWAS) (Ministry of Education, Ghana Education Sector Analysis, 2018a, pg. 11). However, a significant challenge to the beneficial effects of education is the risk of inefficient resource utilization (Worthington, 2001). When educational resources are not managed efficiently and effectively, the outcome may be the production of substandard skills and suboptimal competencies, hindering the development of individuals and societies (Agasisti et al., 2022).

As highlighted in the Ministry of Education, Ghana Education Sector Performance Report (2018b), the significant public expenditure on education, alongside the relatively low academic performance, requires further evaluation of the efficiency and effectiveness of educational institutions in Ghana. Since policymakers mostly rely on academic achievements, as reflected in examination grades, to make informed decisions, there is a need for a more comprehensive assessment of the performance of educational institutions. This is especially important because examination results, often presented in league tables, frequently fail to consider factors beyond the control of schools (Thanassoulis & Dunstan, 1994). Consequently, schools which admit above average ability pupils will have an unfair advantage over their counterparts (Thanassoulis & Dunstan, 1994). Therefore, in search of a more impartial and comprehensive way to compare the performance of schools, there has long been a call for the use of methodologies that allow the contextualization of the examination results by considering elements like students' academic aptitude at the time of enrolment and their socioeconomic background (Thanassoulis & Dunstan, 1994).

The assessment of efficiency in education is commonly approached using two primary methodologies to establish the efficiency frontier: parametric and nonparametric techniques. Within the parametric category, stochastic frontier analysis (SFA) stands out as one of the most widely used by researchers. In terms of the nonparametric approaches, the data envelopment analysis (DEA) technique is probably the most extensively used for assessing the efficiency of educational institutions, systems, and activities (Liu et al., 2013).

Data envelopment analysis is a mathematical programming approach that identifies the production frontier of a decision-making unit (DMU), such as a school, by utilizing available data and specific assumptions regarding the production process (Ruggiero, 2000). This approach constructs a boundary that encompasses all efficient observations, along with linear combinations derived from these efficient units. Observations classified as inefficient are positioned within this boundary. The resulting boundary represents the efficient technology frontier, and the gap between inefficient units and this frontier serves as an indicator of inefficiency (Muñiz, 2002). As a non-parametric technique, DEA tends to measure the efficiency of DMUs by comparing data from multiple input variables (i.e., resources) with data from multiple output variables (i.e., results). All the observed input and output data are used by DEA to form the production possibility frontier. As some of the inputs and outputs can be more relevant than others and their relative importance might vary from DMU to DMU, DEA offers decision-makers the flexibility to assign specific weights to inputs and outputs (Muñiz, 2002).

DEA is the method of choice for this study. One of the primary reasons for this decision is that DEA can manage various inputs and outputs, which is particularly important in the field of education where the production function involves multiple resources and generates a range of results and outcomes (Amado & Dyson, 2009). DEA has also proven useful in providing new insights on previously analyzed activities and entities through alternative methods (Cooper et al., 2011). Additionally, DEA does not require a predetermined functional form for the production function and allows different DMUs to assign varying weights to their inputs and outputs. This flexibility reflects the diversity in the missions of the DMUs and the unique characteristics of non-market activities, such as those in the education sector (Seiford & Thrall, 1990). DEA can also accommodate multiple inputs and outputs measured in different units, even when unit prices are unavailable (Amado & Dyson, 2009), as is often the case in education. Finally, as noted by Agasisti et al. (2014, p. 122), “most of the studies on technical efficiency in schools have employed DEA as their preferred methodological approach.”

Despite the aforementioned advantages, we acknowledge that the DEA technique has some drawbacks. Because no DEA model can account for all possible factors, potentially misleading results might be produced. There is also a risk that managers and practitioners might intentionally suggest or include characteristics that will help their classification (Amado & Dyson, 2009). This concern leads us to advocate for the use of DEA in formative evaluation, so that frank discussions are held with the stakeholders participating in the study to account for the characteristics considered to be most pertinent to the analysis. Furthermore, traditional DEA models do not account for stochastic variation in the data, which can make DEA conclusions susceptible to errors. However, these drawbacks can be mitigated through discussions and meetings with school administrations, as well as by adopting a super-efficiency approach to eliminate outliers (Amado & Dyson, 2009).

In this paper, our objective is to explore the use of DEA for the formative evaluation of senior high schools (SHS) in Ghana and to explore how DEA results can contribute to enhancing their performance. This research is particularly relevant to the knowledge-based economy, as it assesses the efficiency and effectiveness of schools, which play a fundamental role in human capital development (Solarin, 2024). By identifying best practices among SHS and establishing benchmarks for improvement, this study contributes to knowledge creation, diffusion, and application in the education sector—key drivers of economic growth in knowledge economies.

Specifically, the paper aims to measure the relative efficiency and effectiveness of SHS in Ghana using data from the 2020 academic year; identify the best practices among SHS in Ghana, so they can serve as benchmarks for improving the performance of other schools; analyze the underlying factors that contribute to these best practices, providing insights into why some schools perform better than others; and propose policy recommendations and actionable measures to improve SHS performance, strengthening the capacity of Ghana's education system to produce a skilled workforce.

To the best of our knowledge, no published study has applied DEA to evaluate SHS in Ghana in terms of both efficiency and effectiveness. Furthermore, by using country-specific data, this study provides robust insights into school and student performance, offering valuable policy implications for education and workforce development. Also, by using data on national examination results, the study reflects students' actual achievements, which are developed incrementally over the three years they spend in SHS—highlighting the importance of cumulative knowledge acquisition in driving better outcomes.

Additionally, this research makes a methodological contribution by integrating three DEA dimensional models with the hierarchical categorization technique proposed by Cooper et al. (2007). This approach enhances the comprehensiveness of performance evaluation in secondary education and introduces a novel analytical framework for assessing institutional efficiency and effectiveness in a knowledge-driven economy.

Furthermore, it has the potential to contribute across multiple economic levels. At the macrolevel, it supports systemic improvements in Ghana's education system, a key driver of economic development. At the mesolevel, it enhances organizational performance by focusing on SHS institutions as the units of analysis. Finally, at the microlevel, it provides insights that can improve individual student outcomes through better resource allocation and management practices.

The structure of the rest of this paper is organized in the following way. The "Introduction" section discusses and justifies the relevance of the topic and of the DEA technique. The "Previous Research" section provides a review of the empirical literature. The "Methodology and Models" section provides a short theoretical discussion of the methodology and models used. The "Empirical Application" section presents the data and offers a discussion of the results. Insights on how DEA can be used to help some of the schools improve their performance are also offered. The "Concluding Remarks and Policy Recommendations" section offers a summary of key insights and discusses their policy relevance.

Previous Research

DEA has been widely used to estimate efficiency and effectiveness of education entities in many countries with diverse social, economic and cultural backgrounds. While this section focuses on secondary schools, DEA has also been used to assess the performance of universities (e.g., Chen et al., 2024; Loganathan & Subrahmanya, 2023) and broader innovation-education systems (e.g., Liu et al., 2024), highlighting its relevance in evaluating knowledge-based institutions. Assessing and benchmarking the performance of education entities play a central role in the knowledge economy by fostering human capital development, enhancing cognitive skills, and promoting economic growth through innovation and the efficient allocation of resources in knowledge production and application (Hanushek & Woessmann, 2008).

There are various country-specific studies on the efficiency of secondary schools, as well as cross-country studies using international examinations such as the Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA). Some examples of these international studies are discussed below.

For example, Aparicio et al. (2021) compare the group performance of eight European Union countries, specifically examining Public Funded Private Schools (PFPS) and Public Schools (PS) using 2009–2015 PISA data. In their research, they apply an extended version of the one-period Malmquist index by Camanho and Dyson (2006) and the pseudo-panel Malmquist index developed by Aparicio et al. (2017) and Aparicio and Santin (2018). Their study shows that PFPS tend to perform better in Belgium, Ireland, the Netherlands, and Spain. However, in the Czech Republic, Hungary, and Slovakia, PS demonstrate higher productivity than PFPS. In Denmark, the performance gap between the two school types is nearly non-existent. The authors conclude that, although PS are less efficient, they are more productive than PFPS and that increased school autonomy positively influences school performance.

Agasisti and Zoido (2019) adopt a different international perspective, focusing on OECD nations. They examine the efficiency of secondary schools using a dataset from PISA 2012, which covers 30 countries and includes data from 8500 schools. A two-step bootstrap DEA model is used. The initial stage involves using inputs such as the students' socio-economic status, the student-to-teacher ratio, and the number of computers per student, with outputs being the PISA results in language and mathematics. The second stage incorporates variables related to school practices, as well as characteristics of both the school and the students. They estimate an international efficiency frontier at 0.73, implying a 27% inefficiency. They also observe that inefficiency levels differ both between and within countries, with figures ranging from 15% in Singapore to 33% in Slovenia. The findings also reveal more variation in efficiency within countries than between them, as well as lower efficiency in schools with a higher percentage of students from disadvantaged socio-economic backgrounds. Ucar and Karsak (2023) also assess education efficiency of OECD countries using the PISA database (year of 2018) but use common-weight DEA-based models.

In the context of country-specific studies, Henriques and Marcenaro-Gutierrez (2021) use the DEA hybrid approach to assess performance of secondary schools in Portugal using PISA 2015 data. The authors apply the Weighted Russell Directional Distance method and develop a model that demonstrates the equivalence between this DEA approach and the super-ideal point model. The study reveals that the average efficient Portuguese public school achieves mean scores in all areas higher than the national average but still falls short of the OECD's average. It also highlights that schools with the lowest efficiency ratings generally require more effort to enhance reading performance than to enhance mathematics and science competencies. Their results also indicate that schools frequently selected as references for best practices, and classified as efficient, do not necessarily achieve high test scores. This highlights the need to seek new benchmarks that are more consistent with the preferences of decision-makers.

For Tunisia, Rebai et al. (2020) examine the primary factors influencing the academic performance of schools. They use a two-stage analytical process, drawing on data from a sample of secondary schools. In the first stage, they apply the Directional Distance Function method to handle undesirable outputs. In the second stage, machine learning techniques like regression trees and random forests are employed to uncover and visualize variables related to high school performance, based on PISA 2012 survey data. Their findings suggest that key factors influencing higher performance include school size, competition, class size, parental pressure, and a higher proportion of girls in the school. Among all the factors examined, the location of the school seems to have no effect on its efficiency.

Essid et al. (2014) also examine the productivity, efficiency, and technical change in Tunisian schools using the bootstrapped Malmquist Productivity Index approach with quasi-fixed inputs over the academic years 2000/2001 to 2003/2004. Their findings indicate that there is almost no notable change in productivity across the periods examined.

Margaritis et al. (2022) examine the efficiency and productivity changes of upper secondary schools in Central Greece between 2015 and 2018, revealing considerable resource waste and scale inefficiencies.

Silva et al. (2020), in turn, benchmark secondary schools based on students' results in higher education, with a sample of first year students enrolled in the University of Porto and Catholic University of Porto, Portugal, in the 2013/14, 2014/15, and 2015/16 academic years. The study is in reference to the students' secondary schools' results from 65 first-degree programmes. The findings reveal a significant disparity between the rankings of schools according to their capacity to prepare students for higher education success and those based on national exam outcomes. Furthermore, the composite index used in the analysis suggests that the top-performing units face trade-offs between conventional performance metrics and the recently introduced performance measure.

For New Zealand, Alexander et al. (2010) analyze the efficiency of 324 secondary schools by applying a two-stage double bootstrap DEA method. Their findings suggest that teaching quality, including both qualifications and experience, significantly enhances efficiency. In addition, they observe that single-sex schools outperform co-educational schools. Furthermore, they report that state schools tend to show lower performance compared to semi-private schools.

Burney et al. (2013) assess the technical and allocative efficiency across various tiers of public schools in Kuwait. Their findings suggest that factors such as teacher salaries, quality, experience, and the proportion of local-born teachers influence the efficiency of these schools.

Lastly, Minuci et al. (2019) estimate the technical efficiency of 55 county public schools in West Virginia district to find out if they are cost efficient. Their results indicate that the typical school district in West Virginia functions at 93% efficiency, significantly surpassing the average seen in comparable studies, and that the socio-economic status of students plays a pivotal role in determining technical efficiency.

From the previous research outlined, it is evident that country-specific factors and socio-economic variables shape educational efficiency and effectiveness, influencing knowledge dissemination and skill formation. This is particularly relevant to the knowledge economy, where the performance of education systems directly impacts workforce competitiveness and innovation potential. In this regard, further exploration of secondary school efficiency and effectiveness is essential, especially in Ghana, where studies applying DEA in the education sector remain scarce. In fact, as previously mentioned, we are not aware of any prior studies using DEA to assess SHS in Ghana. By evaluating the performance of SHS in Ghana in terms of the efficiency and effectiveness of the services they provide, this study contributes not only to country-specific knowledge but also to the broader discourse on the determinants of higher performance. Ultimately, this research supports the ongoing efforts to enhance knowledge creation, diffusion, and application in the education sector, strengthening its role in the knowledge-based economy.

Methodology and Models

In this section, we present the methodology and the models used to achieve the objectives of the research.

The Data Envelopment Analysis Technique

Building on Farrell's (1957) ideas and the need to improve methods for evaluating the efficiency and productivity of production units, Charnes et al. (1978) developed a non-parametric frontier technique known as Data Envelopment Analysis (DEA). This method was later extended by Banker et al. (1984). The original model became known as the CCR model, while the extended model is referred to as the BCC model. The CCR model is based on the assumption of constant returns to scale (CRS), whereas the BCC model operates under the assumption of variable returns to scale (VRS). A CRS assumption indicates that outputs change proportionally with changes in inputs, while a VRS assumption reflects the possibility that the production technology can show increasing, constant, or decreasing returns to scale.

When using DEA, the relative efficiency scores for each DMU are determined by the ratio of the weighted sum of outputs generated to the weighted sum of inputs employed (Charnes et al., 1978). DEA evaluates DMUs in relative terms based on efficiency ratings (≤ 1 or $\leq 100\%$). A score of 1 or 100% indicates that the DMUs are efficient and are used to define the frontier of the production possibility set (PPS) (Margaritis et al., 2022). A DMU with an efficiency score below 100% is considered inefficient relative to other units and has the potential to improve its efficiency (Margaritis et al., 2022).

Model 1 below presents the original DEA formulation developed by Charnes et al. (1978), where Eff_0 is the efficiency of DMU_0 under analysis; y_{rj} and x_{ij} are the outputs and inputs of DMU j, respectively; and v_i and u_r are the weights for the inputs x_i and outputs y_r, respectively, to be determined for each DMU j_0; j represents the n DMUs in the sample; j_0 stands for the DMU under analysis; and there are s outputs and m inputs.

$$\begin{gathered} \max \mathrm{Eff}_0 = \frac{\sum_{r=1}^{s} u_r y_r j_0}{\sum_{i=1}^{m} v_i x_i j_0} \\ \text{subject to :} \\ \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1; j = 1, \dots, n \\ u_r, v_i \geq 0; r = 1, \dots s; i = 1, \dots, m \end{gathered} \tag{1}$$

The model above can be expressed in a DEA output-oriented model in its "weight formulation" which corresponds to the CRS formulation also known as the CCR model (Charnes et al., 1978). The mathematical formulation used to determine the relative radial efficiency score for each DMU is outlined in (2). By solving this linear programming production problem with output orientation, the maximum radial efficiency score for a specific DMU_0 ($z_0 = 1/k_0$), as well as the optimal weight values for each input (v_i) and output (u_r), can be derived, as described by Charnes et al., (1978: 432):

$$\begin{gathered} \min k_0 = \sum_{i=1}^{m} v_i x_{i0} \\ \text{subject to :} \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0; j = 1, \dots, n \\ \sum_{r=1}^{s} u_r y_{r0} = 1 \\ u_r, v_i \geq 0;\ r = 1, \dots, s; i = 1, \dots, m \end{gathered} \tag{2}$$

We can also solve the dual linear programming formulation of problem (2) to identify the benchmarks and the targets for improvement in the efficiency scores using the formulation (3) (Charnes et al., 1978: 431, 432). The equation derived in model (3) corresponds to the DEA output-oriented model under the CRS assumption developed by Charnes et al. (1978).

$$\begin{gathered} \max p_0 \\ \text{subject to:} \\ -\sum_{j=1}^{n} y_{rj} \lambda_j + y_{r0} p_0 \leq 0; r = 1, \dots, s \\ \sum_{j=1}^{n} x_{ij} \lambda_j \leq x_{i0}; i = 1, \dots, m \\ \lambda_j \geq 0; j = 1, \dots, n. \end{gathered} \tag{3}$$

In this case, the intensity vector λ represents the set of best practices for the efficient frontier that serve as benchmarks for DMU_0, which is currently being evaluated. Model 3 will run for all DMUs to determine the best practice DMUs, which will be identified as benchmarks. These benchmarks are assigned a score of 1 or 100% (i.e., p_0= 1) at the optimal solution. The other DMUs will receive an overall efficiency measure that is positive but less than 1 or 100% (i.e., 0 < $(1/p_0)$< 1) (Charnes et al., 1978).

The DEA technique can also be used to assess the effectiveness of resource utilization by entities (De Witte & López-Torres 2017; Karagiannis & Paschalidou, 2017; Santos et al., 2020). Given that education consistently has an acceptable level of desired outcomes, the effective use of resources in this sector has become paramount (De Witte & López-Torres, 2017). By comparing the resources used with the outcomes achieved, a measure of resource effectiveness can be obtained. However, it is also possible to use DEA to measure effectiveness based solely on the outcomes of DMUs, without considering the inputs used in the production process. This approach was first proposed by Cherchye et al. (2007) and is known as the Benefit-of-the-Doubt (BoD) method. In this approach, the relative effectiveness score is obtained from the weighted sum of outcomes, where any DMU that scores 100% is considered effective and helps define the best practice frontier for the outcomes achieved (Cherchye et al., 2007).

In the calculation of effectiveness scores for DMUs using the BoD approach, let α represent the input weight, and δ_k denote the weight assigned to outcome k. w_{k0} represents the amount of outcome K obtained by DMU_0. The optimal value assigned to the input weight in the evaluation of DMU_0 indicates the greatest radial expansion applicable to all outcomes of that unit (f_0). As described by Zanella et al. (2013), the relative effectiveness score for DMU_0 (calculated as $1/f_0$) and the corresponding optimal weights for the dummy unitary input and each outcome can be determined by solving the following output-oriented model:

$$\begin{gathered}
\text{Min } \alpha = \mathrm{f}_0 \\
\text{subject to:} \\
\textstyle\sum_{k=1}^{q} \delta_k w_{k0} = 1 \\
\textstyle\sum_{k=1}^{q} \delta_k w_{kj} - \alpha \le 0; j = 1, \ldots, n \\
\alpha \ge 0 \\
\delta_k \ge 0; k = 1, \ldots, q.
\end{gathered} \tag{4}$$

Theoretical developments have also demonstrated that the conventional CRS and VRS DEA models can be improved by including supplementary technological judgements, either through production trade-offs in the envelopment DEA models or by applying weight constraints in the dual multiplier models (Podinovski, 2007).

One of the desirable techniques to use is the trade-off approach introduced by Podinovski (2004). This method converts realistic production trade-offs into equivalent weight constraints, ensuring that the radial targets of inefficient units are always attainable (Podinovski, 2004: 1311). To illustrate, consider a scenario where we have K judgements that reflect production trade-offs between inputs and/or outputs. Each of these K judgements can be described as vectors ($C_t \in R^m$, $D_t \in R^s$), which correspond to the input set and the output set, respectively, where

$t = 1, 2, \ldots, K$. Furthermore, let us also assume that these judgements are represented by homogeneous weight restrictions in the following form:

$$\sum_{r=1}^{s} u_r D_t - \sum_{i=1}^{m} v_i C_t \leq 0; t = 1,2, \ldots, K \tag{5}$$

As indicated in Podinovski (2004), in this scenario, the output-oriented CRS envelopment model can be represented as follows:

$$\begin{array}{c} \max z_0 \\ \text{subject to :} \\ \sum_{j=1}^{n} y_{rj}\lambda_j + \sum_{t=1}^{K} \pi_t D_t \geq y_{r0} z_0;\ r = 1, \ldots, s \\ \sum_{j=1}^{n} x_{ij}\lambda_j + \sum_{t=1}^{K} \pi_t C_t \leq x_{i0}; i = 1, \ldots, m \\ \lambda_j, \pi_t \geq 0; j = 1, \ldots, n \text{ and } t = 1, \ldots, K \end{array} \tag{6}$$

The inclusion of the weight restrictions expands the PPS and increases the discrimination in the assessment (Podinovski, 2004). As a result, it is crucial to establish the restrictions based on feasible production trade-offs for all units involved. To demonstrate how these homogeneous restrictions can be interpreted as production trade-offs, let us consider a scenario with two inputs and two outputs, represented by the following judgement vectors: $C_1 = [0, 0]^T$ and $D_1 = [1, -1]^T$. This judgement can be represented by the following homogenous restriction for the two outputs under assurance region type 1 (AR type 1):

$$u_1 - u_2 \leq 0$$

This indicates that output 1 does not require more resources than output 2. Thus, if output 1 increases by one unit while output 2 decreases by one unit, the total resources remain unchanged. Similarly, consider another judgement expressed by the vectors: $C_2 = [-1, 1]^T$ and $D_2 = [0, 0]^T$ for two inputs and two outputs, respectively. This judgement can be represented by the following homogeneous restriction concerning the two inputs (AR type 1):

$$v_1 - v_2 \leq 0$$

This implies that the outputs should not decrease when substituting one unit of input 1 with one unit of input 2 (input 1 decreases by one unit, while input 2 increases by one unit).

DEA Model Specification

Our primary research objective was to conduct a formative evaluation of SHS in Ghana. To achieve this, we decided to engage with stakeholder groups to assess their interest in participating in the research project. Initial visits were made to the Ghana Education Service in the Central Region to meet with management and inquire about their interest. The idea was met with a warm reception, since the research work aimed to assess the state of the SHS performance and suggest strategies to ensure that the objectives of the SHS education are achieved. Following further consultations, the research scope expanded at the national level to include additional regions in Ghana.

In January 2021, we reached out to the Director of Research and Statistics Information Management (RSIM) of the Ghana Education Service in Accra and the Head of the SHS Inspectorate Board to discuss the possibility of scheduling a meeting with them. The initial phase of the study included a meeting with the previously mentioned groups to explore their willingness to participate in the research.

The next stage of the research process involved a meeting with three management staff of RSIM and two members of the SHS Inspectorate Board to discuss the details of the research and the data that would be needed for the research. The meeting lasted for approximately 65 min, covering topics such as the research goals, the methods to be applied, and the key concepts associated with performance evaluation in education.

From the generated ideas, a final conceptual framework was developed for the formative evaluation of SHS in Ghana, incorporating three DEA models as illustrated in Fig. 1.

In what follows, we discuss how these models and theoretical developments were used in the specific context under analysis:

Model 1 intends to measure the resource efficiency of schools through the comparison of school inputs (resources) with school outputs (total number of enrolled students). The aim of the resource efficiency model is to measure the extent to which a school can use the available resources to maximize the number of registered students (in each of the three years), considering its current scale.

Model 2 intends to compare the resources used by third year students in each school (inputs) with the number of students that obtained grades A1, B2, B3, C4, C5, C6, D7, and E8 (outcomes) (where A1 is the highest grade, and E8 the lowest grade) in Social Studies, English, Mathematics, and Science to evaluate the resource effectiveness of each school. The aim of the resource effectiveness model is to measure the extent to which a school can use the available resources to maximize the number of third year students that achieve good results in the final exams, considering its current scale.

In turn, Model 3 measures the effectiveness of each school by holding the inputs to a constant value of 1 to evaluate the outcomes of the third year students results (percentage of students that obtained grades A1, B2, B3, C4, C5, C6, D7, and E8 in Social Studies, English, Mathematics, and Science). The aim of the effectiveness model is to measure the extent to which a school can maximize the proportion of third year students that achieve good results in the final exams, considering its current scale.

The choice of variables was guided by previous studies on efficiency in education (e.g., Worthington, 2001; Huguenin, 2015; and De Witte & López-Torres, 2017) and followed the suggestions of Thanassoulis and Dunstan (1994), who emphasize that when using DEA to measure the efficiency and effectiveness of schools, this choice should be based on research identifying factors that impact exam success and on the available data for the institutions being evaluated.

MODEL 1
Resource Efficiency

INPUTS

X_1: Number of teachers (TCH)
X_2: Number of non-teaching staff (NTCH)
X_3: Number of classrooms (CLS)
X_4: Number of science labs, computer labs, and libraries (SCL)
X_5: Number of administration and staff rooms (ASRM)
X_6: Number of desktop and laptop computers (SODL)
X_7: Number of printers (PNT)

OUTPUTS

Y_1: Number of SHS students in the 1^{st} year (SHS 1)
Y_2: Number of SHS students in the 2^{nd} year (SHS 2)
Y_3: Number of SHS students in the 3^{rd} year (SHS 3)

MODEL 2
Resource Effectiveness

INPUTS

X_8: Number of teachers dedicated to 3^{rd} year students (TCH3)
X_9: Number of non-teaching staff dedicated to 3^{rd} year students (NTCH3)
X_{10}: Number of classrooms dedicated to 3^{rd} year students (CLS3)
X_{11}: Number of science labs, computer labs, and libraries dedicated to 3^{rd} year students (SCL3)
X_{12}: Number of administration and staff rooms dedicated to 3^{rd} year students (ASRM3)
X_{13}: Number of desktop and laptop computers dedicated to 3^{rd} year students (SODL3)
X_{14}: Number of printers dedicated to 3^{rd} year students (PNT3)
X_{15}: Number of SHS students in the 3^{rd} year (SHS 3)

OUTCOMES

Z_1- Z_8: Number of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Social Studies (Z_1=SocA1…Z_8=SocE8)
Z_9-Z_{16}: Number of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in English (Z_9= EngA1 … Z_{16}=EngE8)
Z_{17} -Z_{24}: Number of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Math (Z_{17}=MatA1…. Z_{24}=Mat E8)
Z_{25}- Z_{32}: Number of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Science (Z_{25}= SciA1 … Z_{32}=SciE8)

MODEL 3
Effectiveness

INPUTS

X_{16}: Dummy=1 (UNINPUT)

OUTCOMES

W_1- W_8 : Percentage of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Social Studies (W_1=SocA1…W_8=SocE8)
W_9-W_{16}: Percentage of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in English (W_9= EngA1 … W16=EngE8)
W_{17} -W_{24}: Percentage of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Math (W_{17}=MatA1…. W_{24}=Mat E8)
W_{25}- W_{32}: Percentage of SHS students in the 3^{rd} year that got A1; B2; B3; C4; C5; C6; D7; E8, respectively, in Science (W_{25}= SciA1 … W_{32}=SciE8)

Fig. 1 Framework for the performance evaluation of secondary (senior high) schools in Ghana

As shown in Fig. 1, the inputs in Model 2 are similar to those in Model 1, with two key exceptions. First, the inputs in Model 2 refer only to the share of resources allocated to third-year students. We estimated this amount by multiplying the resources used in each school by the proportion of third-year students enrolled in that school. Second, Model 2 includes an additional input, the "Number of SHS students in the third year," to ensure feasible targets.

It is also important to highlight that in the resource effectiveness and effectiveness models (Models 2 and 3, respectively), we only include outcomes related to students who passed the exams. This is because the objective is to reward schools that successfully prepare students for passing. In this case, students who attempt the exams but fail (final score of F9: 0–39%) are not considered.

As part of the methodological procedure adopted, we mimic the method of hierarchical categorization proposed by Cooper et al. (2007 p. 227) to offset the advantages that DMUs may enjoy over their peers in the evaluation process. In our study, schools are categorized according to their entry qualification grades. We have schools in category “A” (the most favorable context, as these schools enroll the students with the highest grades); schools in category “B” (the intermediate context); and schools in category “C” (the least favorable context, as these schools enroll the students with the lowest grades). In this respect, we evaluate category “A” schools against all schools (A, B, and C) in the technology set. Then, we evaluate schools from category “B” against the schools from categories “B” and “C” in the technology set. Lastly, we evaluate schools in category “C” only against the schools in category “C” in the technology set. In this way, we guarantee that schools are compared only to those that have similar or more difficult contexts. This method fairly compares the schools in an appropriate manner so that producible benchmarks are displayed (Cooper et al., 2007). It is important to highlight that Category “A” schools, which are termed as “the best schools,” have very demanding admission requirements, and parents tend to prefer to enroll their kids into these “best” schools. This means that less demanding schools, who admit average students, will be at a disadvantage if they are initially compared together.

Furthermore, we use an output-oriented model for all the three DEA models. The output orientation was considered preferable as it highlights the additional outputs (or outcomes) needed for a specific underperforming DMU (here, schools) to reach the efficiency (or effectiveness) level of the best practices. We have chosen the output-oriented version also because we believe that it aligns more closely with the objectives of the Ghana Education Service policymakers, who appear to prioritize enhancing educational outputs rather than reducing educational inputs.

In the analysis, weight restrictions on the input, output, and outcome variables were introduced using the trade-off approach proposed by Podinovski (2004) to generate realistic and meaningful results while enhancing the discriminatory power of the DEA models. As mentioned previously, the trade-off approach also has the advantage of allowing the performance scores to maintain their radial interpretation. Furthermore, following Dyson et al. (2001), we also defined restrictions to prevent a variable from having a weight more than 1000 times greater than the weight of another variable. See Appendix A in the Supplementary Material for the complete list of weight restrictions included in the models.

Empirical Application

A Brief Discussion of Ghana’s Education System

Ghana’s current post-kindergarten education begins at the age of six and follows a 6–3–3–4 system: six years of primary school, three years of junior high school (JHS), three years of senior high school, and four years of university. Junior high school serves as the transition from basic to secondary education. Its primary goal is to introduce students to fundamental scientific and technical knowledge and skills. It also prepares them for more advanced academic studies or vocational training at the senior high school level. Upon completing JHS, students sit for the Basic Education Certificate Examination (BECE) to determine their eligibility for senior high school (Adu-Gyamfi et al., 2016).

Senior high schools in Ghana enroll qualified students to build on the knowledge acquired in junior high school. After the three-year SHS programme, all students take the West African Senior School Certificate Examination (WASSCE), which assesses them in seven or eight subjects. These include four compulsory core subjects: Mathematics, Integrated Science, Social Studies, and English Language, as well as three or four elective subjects selected from one of seven categories: General Science, Agricultural Science, Home Science (formerly Home Economics), Visual Arts, General Arts, Business, and Technical Subjects. Students who pass the WASSCE are eligible to pursue higher education at a university, technical university, college of education, or other tertiary institutions (Adu-Gyamfi et al., 2016). WASSCE grades range from A1 (the highest) to F9 (the lowest), with a minimum average score of C6 (credit) required in each subject for admission to further education (Adu-Gyamfi et al., 2016).

The School Sample and Data

The analysis in the next sections is based on 215 public senior high schools from five regions of Ghana (Greater Accra Region, Ashanti Region, Central Region, Upper West Region, and Upper East Region) and the schools are classified into A, B, and C according to the "entrance standard of pupils" examination scores obtained from junior high schools.

Since the DEA technique is sensitive to measurement errors, we decided to investigate whether certain schools can be classified as super-efficient (i.e., whether they differ significantly from other schools) using the model proposed by Andersen and Petersen (1993). A school may be identified as super-efficient either because it has performed much better than other schools in the dimensions analyzed, or possibly due to measurement error. As these schools shift the best practice frontier to a very high level, it is preferable to remove them if the data is contaminated by noise to obtain more realistic results (Banker & Chang, 2006). Therefore, in this study, schools identified as super-efficient were excluded from subsequent efficiency and effectiveness model computations. Specifically, schools with a super-efficiency score above 120% were considered outliers and removed from the analysis, as proposed by Banker and Chang (2006). According to Banker and Chang (2006) and Banker et al. (2017), this method is effective in practical applications. To identify outliers, we ran each of the three models separately, following the procedure proposed by Cooper et al. (2007: 227). Our initial sample included 228 schools (24 in category A, 85 in category B, and 119 in category C). However, a total of 13 different schools were identified as outliers in at least one of the three models. Three outliers belonged to schools in category A, four outliers belonged to schools in category B, and the remaining six outliers belonged to schools in category C. Our final sample consists, therefore, of 215 schools (21 in category A, 81 in category B, and 113 in category C).

The data for the research were obtained from the databases of the West African Examinations Council (WAEC), the Research and Statistics Information Management (RSIM) Directorate of Ghana and the Ghana Education Service (GES). The inclusion of five regions in the analysis was based on data availability, with the 2019/2020 academic year used as the reference. Tables 1, 2, and 3 list the input, output, and outcome variables employed in the three DEA models and their corresponding summary statistics.

Results Presentation and Discussion

In this section, we present and discuss the results obtained from the three different models using and output-orientation and the VRS assumption. In specific, Table 4 presents a summary of the results of the schools' relative resource efficiency, resource effectiveness and effectiveness, obtained using the Efficiency Measurement System (EMS) software, version 1.3, developed by Scheel (2000). Tables 5 presents, in turn, the overall results by school category. The results by school are available in Appendix B of the Supplementary Material.

Relative Resource Efficiency (Pure Technical Efficiency)

In Model 1, the results from 215 schools reveal that 33 schools are pure technical efficient, representing about 15.35% of the schools analyzed. This indicates that they use their resources with 100% efficiency. These schools are as follows: Agona SHS, Asanteman SHS, Bankoman SHS, Islamic SHS Kumasi, Osei Tutu SHS, St. Jerome SHS, Achinakrom SHS, Adu Gyamfi SHS Jamasi, Agogo State SHS, Dadease Agricultural SHS, Ejisu SHTS, Jacobu SHTS, Kofiase Adventist SHTS, Kumasi SHTS, Mansoman SHS, Nyinahin Catholic SHS, Zorkor SHS, Islamic SHS Wa, Assin North SHTS, Brakwa SHTS, Siddiq SHS, Abakrampa SHTS, Owerriman

Table 1 Summary statistics for the variables used in Model 1 (year 2020)

Variables	Average	St. deviation	Min	Max
X_1—number of teachers	94.73	34.97	24	203
X_2—number of non-teaching staff	41.58	17.10	8	84
X_3—number of classrooms	37.73	15.17	8	91
X_4—number of science labs, computer labs and libraries	5.39	2.61	2	21
X_5—number of administration and staff rooms	11.25	4.07	5	23
X_6—number of desktop and laptop computers	47.21	28.64	16	158
X_7—number of printers	3.12	2.04	1	15
Y_1—number of SHS students in the 1st year	698.97	345.60	88	2600
Y_2—number of SHS students in the 2nd year	762.72	442.51	123	2908
Y_3—number of SHS students in the 3rd year	586.38	236.15	100	1798

Table 2 Summary statistics for the variables used in Model 2 (year 2020)

Variables	Average	St. deviation	Min	Max
X_8—number of teachers dedicated to 3rd year students	27.47	9.64	4.61	59.19
X_9—number of non-teaching staff dedicated to 3rd year students	11.91	4.40	1.65	25.19
X_{10}—number of classrooms dedicated to 3rd year students	10.96	4.12	2.05	21.90
X_{11}—number of science labs, computer labs and libraries dedicated to 3rd year students	3.66	0.72	2	7.92
X_{12}—number of administration and staff rooms dedicated to 3rd year students	3.28	1.14	1.03	6.74
X_{13}—number desktop and laptop computers dedicated to 3rd year students	13.75	8.20	3.41	52.06
X_{14}—number of printers dedicated to 3rd year students	1.60	0.58	1	4.82
X_{15}—number of SHS students in the 3rd year	586.39	236.15	100	1798
Z_1—number of students that got A_1 in Social studies	22.67	43.67	0	269
Z_2—number of students that got B_2 in Social studies	29.82	38.34	0	250
Z—number of students that got B_3 in Social studies	100.09	83.86	0	390
Z_4—number of students that got C_4 in Social studies	60.60	39.74	0	218
Z_5—number of students that got C_5 in Social studies	47.48	28.42	1	169
Z_6—number of students that got C_6 in Social studies	93.07	48.93	0	289
Z_7—number of students that got D_7 in Social studies	41.50	23.22	0	154
Z_8—number of students that got E_8 in Social studies	48.70	28.87	0	196
Z_9—number of students that got A_1 in English language	2.82	9.44	0	78
Z_{10}—number of students that got B_2 in English language	6.88	18.94	0	145
Z_{11}—number of students that got B_3 in English language	67.33	99.06	0	499
Z_{12}—number of students that got C_4 in English language	30.87	31.93	0	128
Z_{13}—number of students that got C_5 in English language	61.01	52.29	0	233
Z_{14}—number of students that got C_6 in English language	142.67	82.79	6	462
Z_{15}—number of students that got D_7 in English language	113.03	64.08	0	307
Z_{16}—number of students that got E_8 in English language	78.05	56.60	0	267
Z_{17}—number of students that got A_1 in Mathematics	46.62	68.51	0	340
Z_{18}—number of students that got B_2 in Mathematics	48.42	57.76	0	300

Table 2 (continued)

Variables	Average	St. deviation	Min	Max
Z_{19}—number of students that got B_3 in Mathematics	126.64	110.29	0	597
Z_{20}—number of students that got C_4 in Mathematics	32.23	24.30	0	113
Z_{21}—number of students that got C_5 in Mathematics	41.07	30.22	0	142
Z_{22}—number of students that got C_6 in Mathematics	76.40	56.52	0	264
Z_{23}—number of students that got D_7 in Mathematics	60.16	47.46	0	229
Z_{24}—number of students that got E_8 in Mathematics	60.07	53.30	0	250
Z_{25}—number of students that got A_1 in Science	9.13	26.34	0	220
Z_{26}—number of students that got B_2 in Science	12.82	27.02	0	187
Z_{27}—number of students that got B_3 in Science	64.86	93.91	0	496
Z_{28}—number of students that got C_4 in Science	28.72	31.01	0	186
Z_{29}—number of students that got C_5 in Science	48.83	44.90	0	253
Z_{30}—number of students that got C_6 in Science	106.25	74.23	0	342
Z_{31}—number of students that got D_7 in Science	95.02	59.43	0	316
Z_{32}—number of students that got E_8 in Science	84.31	55.82	0	233

Table 3 Summary statistics for the variables used in Model 3 (year 2020). Note: All percentages are represented as decimals (e.g., 0.04 = 4%)

Variables	Average	St. deviation	Min	Max
X_{16}—Dummy unitary input	1	0	1	1
W_1—% of students that got A_1 in Social Studies	0.04	0.07	0	0.58
W_2—% of students that got B_2 in Social Studies	0.05	0.05	0	0.22
W_3—% of students that got B_3 in Social Studies	0.16	0.11	0	0.45
W_4—% of students that got C_4 in Social Studies	0.10	0.05	0	0.28
W_5—% of students that got C_5 in Social Studies	0.08	0.03	0.01	0.21
W_6—% of students that got C_6 in Social Studies	0.16	0.06	0	0.34
W_7—% of students that got D_7 in Social Studies	0.07	0.03	0	0.16
W_8—% of students that got E_8 in Social Studies	0.09	0.04	0	0.18
W_9—% of students that got A_1 in English language	0	0.01	0	0.11
W_{10}—% of students that got B_2 in English language	0.01	0.03	0	0.18
W_{11}—% of students that got B_3 in English language	0.10	0.13	0	0.58
W_{12}—% of students that got C_4 in English language	0.05	0.04	0	0.19
W_{13}—% of students that got C_5 in English language	0.10	0.07	0	0.33
W_{14}—% of students that got C_6 in English language	0.24	0.10	0.02	0.44
W_{15}—% of students that got D_7 in English language	0.20	0.09	0	0.42
W_{16}—% of students that got E_8 in English language	0.14	0.09	0	0.41
W_{17}—% of students that got A_1 in Mathematics	0.07	0.11	0	0.55
W_{18}—% of students that got B_2 in Mathematics	0.08	0.08	0	0.37
W_{19}—% of students that got B_3 in Mathematics	0.20	0.15	0	0.58
W_{20}—% of students that got C_4 in Mathematics	0.05	0.03	0	0.13
W_{21}—% of students that got C_5 in Mathematics	0.07	0.04	0	0.21
W_{22}—% of students that got C_6 in Mathematics	0.13	0.07	0	0.34
W_{23}—% of students that got D_7 in Mathematics	0.10	0.07	0	0.27
W_{24}—% of students that got E_8 in Mathematics	0.11	0.09	0	0.38
W_{25}—% of students that got A_1 in Science	0.01	0.04	0	0.30
W_{26}—% of students that got B_2 in Science	0.02	0.04	0	0.24
W_{27}—% of students that got B_3 in Science	0.10	0.13	0	0.63
W_{28}—% of students that got C_4 in Science	0.04	0.04	0	0.19
W_{29}—% of students that got C_5 in Science	0.08	0.06	0	0.26
W_{30}—% of students that got C_6 in Science	0.18	0.10	0	0.50
W_{31}—% of students that got D_7 in Science	0.16	0.08	0	0.42
W_{32}—% of students that got E_8 in Science	0.15	0.08	0	0.35

SHS, Wesley SHS Bekwai, Daffiama SHTS, Ofoase Kokobin SHS, St. Mary's Girls' SHS Konongo, Adjen Kotoku SHS, Diaso SHS, Tijjaniya SHS Zion, St. Augustine's SHTS, Holy Family SHS, and Birofoh SHS. These schools comprise 9 schools from category B and 24 schools from category C. Remarkably, none of the schools from category A (the presumed "elite schools" that admit the best students) is resource efficient. The results also indicate that the average pure technical efficiency score is

Table 4 Schools relative resource efficiency, resource effectiveness and effectiveness scores

	DEA Model 1 Efficiency	DEA Model 2 Resource effective-ness	DEA Model 3 Effectiveness
No. of efficient/effective schools	33	55	19
% of efficient/effective schools	15.35	25.58	8.83
Average score (%)	80.88	76.25	70.14
Std Dev. (%)	14.00	21.20	21.26
Min (%)	40.42	25.53	20.61
Max (%)	100.00	100.00	100.00

Table 5 Resource efficiency, resource effectiveness, and effectiveness of schools by category

	DEA Model1 Efficiency			DEA Model 2 Resource effectiveness			DEA Model 3 Effectiveness		
School category→	*A*	*B*	*C*	*A*	*B*	*C*	*A*	*B*	*C*
No. of efficient/effective schools	0	9	24	12	22	21	4	7	8
% of efficient/effective schools	0	11.11	43.80	57.14	27.16	18.58	19.04	8.6	7.08
Average score (%)	76.37	78.63	83.34	92.30	82.00	69.14	88.99	76.34	62.19
Std Dev. (%)	12.61	13.59	14.05	12.87	17.90	21.74	12.27	17.70	21.16
Min (%)	40.42	47.57	48.30	59.13	33.27	25.53	58.10	26.39	20.61
Max (%)	95.57	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

80.88% with a standard deviation of approximately 14.0%. Ninety-eight (98) schools representing 45.58% present pure technical efficiency scores below average, indicating that these schools are the ones with most potential for improvement.

These results challenge conventional assumptions about school performance, suggesting that resource efficiency does not necessarily correlate with prestige or selectivity but rather with the strategic deployment of educational inputs. Interestingly, category C schools demonstrate the highest efficiency levels, followed by category B schools, while category A institutions lag behind. This insight underscores the importance of rethinking resource allocation strategies in secondary education to enhance productivity, innovation, and equitable human capital development, key pillars of the knowledge economy.

Resource Effectiveness

Regarding relative resource effectiveness (Model 2), the results show that 55 schools are resource effective, representing 25.58% of the schools analyzed. These schools are: Opoku Ware SHS,Prempeh College, T.I. Ahmadiyya SHS Kumasi, Achimota SHS, St. Mary’s SHS, Notre Dame Seminary and SHS Navrongo, Nandom SHS, Adisadel College, Holy Child SHS, Mfantsiman Girls' SHS, Mfantsipim School, St. Augustine's College, Asanteman SHS, Islamic SHS Kumasi, Konadu Yiadom SHS, Kumasi Academy SHS, Kumasi Anglican SHS, Kumasi Wesley Girls' SHS, Mpasatia SHTS, Nsutaman Catholic SHS, Ofoase Kokoben SHS, Osei Tutu SHS, Sekyedumase SHS, St. Monica's SHS Mampong, T.I. Ahmadiyya SHS Fomena, Labone SHS, Wesley Grammar SHS, Aggrey Memorial A.M.E. Zion SHS, Apam SHS, Awutu Winton SHS, Diaso SHS, Nyakrom SHTS, Swedru SHS, T.I Ahmadiyya SHS Ekumfi, Adu Gyamfi SHS Jamasi, Agogo State SHS, Akumadan SHS, Amaniampong SHS, Antoa SHS, Ejisu SHTS, Ejisuman SHS, Ejuraman Anglican SHTS, Jacobu SHTS, Kwamang Presby SHTS, St. Joseph Seminary SHS, Wesley SHS Bekwai, Armed Forces SHTS Kumasi, 'O' Reilly SHS, Our Lady of Louders Girls' SHS, St. Augustine's SHTS, Assin North SHTS, Assin Nsuta Agric. SHS, Enyan Denkyira SHTS, Oguaa SHTS, and Swedru School of Business. The breakdown of the resource effective schools according to their categories indicates that, out of the 55 schools that are resource effective, 12 schools are from category A, 22 schools are from category B, and 21 schools are from category C. The overall average resource effectiveness is approximately 76.25%, with a standard deviation of about 21.2%. Table 4 also shows a minimum score of 25.53%, indicating that some schools have significant potential for improvement in this area. In fact, 46.98% of the schools, corresponding to 101 schools, fall below the average score of 76.25%, which suggests poor performance in this dimension.

When we compare the average scores across school categories, a different picture emerges from that observed in terms of resource efficiency. In fact, the results leave no doubt that category A schools are the most resource-effective, with an average score of 92.3%, significantly higher than that of category C schools (69.14%). This gap suggests that the entry-level academic grades of students play a crucial role in the resource effectiveness and the broader outcomes of educational institutions, supporting the importance of optimizing human capital for long-term economic development.

Effectiveness

Model 3 investigates the effectiveness of the various categories of senior high schools to know the extent to which a school can maximize the proportion of third year students that achieve good results in the final exams, considering its current scale. The results reveal that 19 schools out of the 215 schools analyzed (i.e. 8.84%) are considered effective. These are Notre Dame Seminary SHS Navrongo, Holy Child SHS, Mfantsipim School, St. Augustine's College, Kumasi Wesley Girls' SHS, St. Monica's SHS Manpong, Labone SHS, Wesley Grammar SHS, Aggrey Memorial A.M.E. Zion SHS, Diaso SHS, Nyakrom SHTS, Akumadan SHS, Ejisu SHTS, Ejuraman Anglican SHTS, Armed Forces SHTS Kumasi, 'O'Reilly SHS, Assin Nsuta Agricultural SHS, Enyan Denkyira SHTS, and Ogua SHTS.

Four of these schools belong to category A, 7 belong to category B, and the remaining 8 belong to category C. The results also reveal that the average effectiveness score is 70.14%, the lowest of the three dimensions, with a standard deviation of 21.26%. It is also important to observe that some schools show considerable potential to improve their effectiveness as the minimum score observed is slightly above 20% (i.e., 20.61%). In fact, this is the dimension where we observe the poorest performance with 102 schools, representing 47.44% of the schools analyzed, performing below the average score, highlighting the need for these schools to develop more effective strategies to improve their performance outcomes.

The results we obtain when comparing the average effectiveness scores across school categories are consistent with the findings related to resource effectiveness. In particular, we observe that schools in category A are the best performers, followed by schools in category B. Schools in category C clearly show the most potential for improvement in this dimension. Overall, these results point to the potential for targeted interventions and innovations to elevate educational outcomes across different types of schools, contributing to overall human capital development.

The Benchmarks

An important aspect of our formative assessment of SHS performance in Ghana is to provide insights that can help lower-performing schools improve. To achieve this, it is essential to identify not only the underperforming schools but also those that can serve as learning platforms by demonstrating top performance. Table 6 presents the summary benchmarks for the three models analyzed, while Table 7 highlights the resource-efficient, resource-effective, and effective schools, along with their respective benchmark counts.

As shown in Table 6, Model 1 (resource efficiency) identifies 28 schools that can serve as benchmarks for other schools, fostering knowledge diffusion across the education sector. These include 7 schools from category B and 21 schools from category C. The results also reveal that there are 5 efficient schools that, despite their efficiency, do not qualify as benchmarks for any other schools. This suggests that these schools follow very specific practices that are not transferable to the other schools assessed. These 5 schools consist of 2 from category B and 3 from category C. As expected, none of the schools from category A serve as benchmarks for any other schools in terms of resource efficiency.

The benchmark results of the resource effectiveness model (Model 2) reveal that, among the schools considered resource-effective, 44 serve as benchmarks for other schools. These benchmark schools include 9 from category A, 16 from category B, and 19 from category C, illustrating the systemic impact of resource-effective practices at both the organizational and individual levels. The resource-effective schools that do not serve as benchmarks include 3 from category A, 6 from category B, and 2 from category C.

Our analysis also shows that out of the 19 effective schools (Model 3), 15 can serve as benchmarks for others, including 2 from category A, 6 from category B, and 7 from category C. The remaining 4 effective schools, despite their 100% score, do not act as benchmarks.

The results further indicate that some schools can serve as benchmarks for a significantly larger number of schools than others and are therefore worth mentioning.

Table 6 Summary of benchmarks for all the three models

Number of schools: 215	Model 1 Efficiency	Model 2 Resource effectiveness	Model 3 Effectiveness
Number of schools that are benchmarks to other schools:	28	44	15
Category A schools	0	9	2
Category B schools	7	16	6
Category C schools	21	19	7
Efficient/effective schools that do not serve as a benchmark:	5	11	4
Category A schools	0	3	2
Category B schools	2	6	1
Category C schools	3	2	1

For example, in the resource efficiency model (Model 1), Agogo State SHS has 58 counts, Jacobu SHTS and Islamic SHS Kumasi have 49 counts, Agonja SHS has 42 counts, and Ejisu SHTS has 37 counts. These results suggest that particular attention should be given to the practices of these schools, as they can provide valuable insights on improving the resource efficiency of underperforming schools.

In Model 2 (the resource effectiveness model), Ejisu SHTS has 71 counts, Kumasi Wesley Girls' SHS has 44 counts, Akumadan SHS has 40 counts, Diaso SHS has 32 counts, and Adu-Gyamfi SHS has 30 counts. Again, these schools, and particularly Ejisu SHTS, represent important case studies.

In Model 3 (the effectiveness model), Ejisu SHTS has 91 counts, Diaso SHS has 60 counts, Kumasi Wesley Girls' SHS has 50 counts, and Ejuraman Anglican SHTS has 48 counts. These values clearly suggest that these schools are potential sources for others to consult and learn from regarding their performance strategies. Table 7 synthesizes this information and shows the categories of the schools that serve as benchmarks for the largest number of other schools. The detailed results by school are displayed in Appendix C of the Supplementary Material.

While various factors can account for the disparities in the school's performance, the findings in the previous sections strongly indicate that exchanging best practices could substantially enhance the performance of SHS in Ghana. This aligns with the broader aim of leveraging knowledge creation and innovation to address challenges in education, fostering systemic improvements across the Ghana's national education system.

For example, in terms of resource efficiency, Kinbu Senior High Technical School underperforms, with a pure technical efficiency score of 71.22%. This indicates that, given its resources during the 2019/2020 academic year, this school should have been able to teach 40% more students in the first, second, and third years. While these targets may seem demanding, a comparison with the benchmark

Table 7 Some selected schools and their benchmark counts

Model 1 Efficiency			Model 2 Resource effectiveness			Model 3 Effectiveness		
School	Cat	Count	School	Cat	Count	School	Cat	Count
Agogo State SHS	C	58	Ejisu SHTS	C	71	Ejisu SHTS	C	91
Jacobu SHTS	C	49	Kumasi Wesley Girls' SHS	B	44	Diaso SHS	B	60
Islamic SHS, Kumasi	B	49	Akumadan SHS	C	40	Kumasi Wesley Girls' SHS	B	50
Agona SHS	B	42	Diaso SHS	B	32	Ejuraman Anglican SHTS	C	48
Ejisu SHTS	C	37	Adu-Gyamfi SHS	C	30	St. Augustine's College	A	17
Nyinahin Catholic SHS	C	35	Enyan Denkyire SHTS	C	23	Armed Forces SHTS, Kumasi	B	10
Bankoman SHS	B	34	St. Augustine's SHTS	C	20	Aggrey Mem. AME Zion SHS	B	7
Assin North SHTS	C	33	Armed Forces SHS	C	15	Akumadan SHS	C	7
Kofiase Adventist SHS	C	27	Mpasatia Catholic SHS	B	14	Enyan Denkyira SHTS	C	7
Brakwa SHTS	C	20	Adisadel College	A	7	St. Monica's SHS, Mampong	B	4

schools—Agogo State Senior High School and Jacobu Senior High Technical School—makes it clear that Kinbu is underperforming relative to its peers.

Although all these schools fall into category B, as shown in Table 8, Agogo and Jacobu manage to teach significantly more students per resource type than Kinbu. For instance, Jacobu has 31.8 students per teacher, whereas Kinbu has only 17.2 students.

Similar conclusions can be drawn when analyzing other performance dimensions. For example, in the dimension of resource effectiveness, where Kinbu scored 40.67%, its benchmarks are Akumadan Senior High School and Ejisu Senior High Technical School. When we compare the proportion of 3rd-year students who passed Social Studies, English, Mathematics, and Science, a clear picture emerges, revealing significant potential for Kinbu to improve and reach the level of its peers. As shown in Table 9, Kinbu's peers not only have considerably more 3rd-year students per teacher, but they also have much higher pass rates in Social Studies, English, Mathematics and Science.

These results illustrate the potential of using DEA formatively to evaluate the performance of educational institutions, offering insights into how data-driven frameworks can inform policy decisions at the systemic, organizational, and individual levels.

Comparing Efficiency Versus Effectiveness and Exploring the Possible Existence of Trade-Offs

Bearing in mind that some schools achieve above-average performance in certain dimensions while underperforming in others, a pertinent question is whether there are trade-offs among the three performance dimensions studied. This question aligns with the evolving role of knowledge and innovation in driving performance across different levels of the education system. The possibility of trade-offs becomes relevant when significant percentages of schools display above-average scores in one performance criterion but below-average scores in others. To explore this issue, we compare the results obtained by each school in terms of resource efficiency (Model 1) and effectiveness (Model 3). Comparing performance results across these two dimensions is important because the resource efficiency model assesses how well a school uses its available resources to maximize the number of students registered over three years, while the effectiveness model examines how well a school maximizes the proportion of third-year students who achieve good results on the final exams.

As shown in Fig. 2, the comparison of results reveals that 55 schools simultaneously exceed the average scores of 80.88% for the pure technical efficiency model and 70.14% for the effectiveness model. These schools fall within the area marked in blue in the upper right corner of the figure and include Asanteman SHS; Osei Tutu SHS; St. Jerome SHS; Adu-Gyamfi SHS; Agogo State SHS; Ejisu SHTS; Jacobu SHTS; Kofiase Adventist SHTS; Siddiq SHTS; Owerriman SHS; Wesley SHS Bekwai; Ofoase Kokoben SHS; Diaso SHS; Ejisuman SHS; Kumasi Academy SHS; T.I. Ahmadiyya Kumasi; Kwamang Presbyterian SHTS; Kusanaba SHS; Bonwire

Table 8 Contrasting the performance of Kinbu SHS with that of its peers in terms of resource efficiency

	Total number of students per						
	Teachers	Non-teaching staff	Classrooms	Science labs, computer labs, and libraries	Administration and staff rooms	Students and office desktops and laptops	Printers
Kinbu Senior High Technical School	17.2	45.5	49.3	296.0	177.6	74.0	888.0
Agogo State Senior High School	31.6	67.6	70.4	675.8	259.9	71.9	1126.3
Jacobu Senior High Technical School	31.8	65.8	70.8	368.4	307.0	96.9	921.0

Table 9 Contrasting the performance of Kinbu SHS with that of its peers in terms of resource-effectiveness

	3rd year students per teacher	Percentage of 3rd year students who have obtained a pass grade in			
		Social Studies	English	Math	Sciences
Kinbu Senior High Technical School	17.24	56.43	83.82	28.86	31.99
Akumadan Senior High School	22.74	85.21	98.96	99.26	99.26
Ejisu Senior High Technical School	29.31	98.17	97.94	98.86	98.86

SHTS; Kumasi Anglican SHS; Enyan Denkyira SHTS; Prempeh College; Swedru SHS; Sekyedumase SHS; Mfantsiman Girls' SHS; Opoku Ware SHS; Kumasi Wesley Girls SHS; Methodist SHS; Oguaa SHTS; Bisease SHS; Apam SHS; St. Thomas Aquinas SHS; Konongo-Odomasi SHS; Kofi Adjei SHTS; Kumasi Girls SHS; Edinaman SHS; T.I. Ahmadiyya SHS,Fomena; Mankessim SHTS; Achimota SHS; Odorgonno SHS; Armed Forces SHTS Kumasi; Collins SHS; St. Monica's

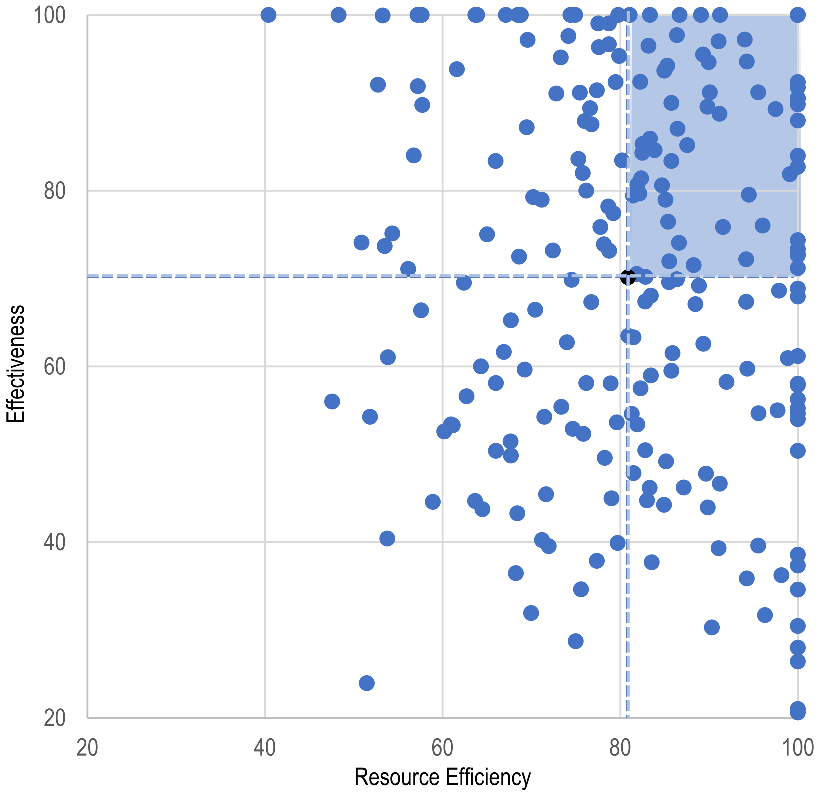

Fig. 2 Comparison of the results of resource efficiency versus effectiveness

SHS, Mampong; T.I. Ahmadiyya Ekumfi; Jirapa SHS; Yaa Asantewaa Girls' SHS; Acca Girls' SHS; T.I Ahmadiyya Potsin; St. Joseph Seminary SHS; Osei Kyeretwie SHS; Odoben SHS; Nungua SHS; Serwaa Nyarko Girls' SHS; 'O' Reilly SHS; and Mpasatia SHTS. These schools include 8 schools from Category A, 26 schools from Category B, and 21 schools from Category C. The results also reveal that only two schools are both purely technically efficient and effective, meaning they score 100% in both Models 1 and 3. These schools are Diaso SHS and Ejisu SHTS. Interestingly, Diaso SHS belongs to Category B, while Ejisu SHTS is from Category C. These two schools represent less than 1% of the schools included in the study, which is suggestive that there is considerable room for improving the performance of senior high schools in Ghana.

Based on Fig. 2 and the analysis performed, we can conclude that although some trade-offs might exist between the three performance dimensions in this context, the fact that a considerable number of schools display above-average performance in all the dimensions considered suggests that this is not a significant issue. In fact, our analysis provides strong evidence that senior high schools in Ghana can be simultaneously resource-efficient, resource-effective, and effective. This insight reinforces the broader understanding of knowledge-driven performance at the organizational level, highlighting how the application of best practices can lead to innovative and sustainable solutions. Therefore, the schools whose practices warrant further exploration are Diaso SHS and Ejisu SHTS, as they are the only ones achieving optimal performance across all three dimensions, showcasing the potential for knowledge innovation and application to solve performance-related challenges in education.

Results of Schools That Score Below Average in All the Three DEA Models

In this section, we present the results for schools that score below the average in all three DEA dimensions considered in this study. In line with the aims of promoting knowledge diffusion and fostering innovation within education systems, we aim to provide actionable insights to policymakers on schools that may benefit from more urgent targeted interventions. These interventions, driven by knowledge-based solutions, could address the challenges faced by underperforming institutions. The results show that 44 schools, representing 20.47% of the schools included in the study, perform below the average scores across all three models. These schools are Sandema SHS, Ko SHS, Manso Adubia SHS, Senya SHS, Chiana SHS, Adanwomase SHS, Awe SHTS, Lawra SHS, Gyaase SHS, Jukwa SHS, Piina SHS, St. Margaret Mary SHTS, Bolgatanga SHS, Kaleo SHTS, Christ the King Catholic SHS, Mozano SHS, Dunkwa SHTS, St. George's Catholic SHS, Kinbu SHTS, T.I. Ahmadiyya Girls' SHS Asokore, Twifo Hemang SHTS, Wa SHTS, Eguafo-Abrem SHS, Manhean SHTS, Mando SHTS, Ashaiman SHS, Bawjiase Community SHS, Bolga Girls' SHS, Obrachire SHTS, Zebilla SHTS, T.I. Ahmadiyya SHS, Twifo Praso SHS, Amasaman SHTS, Paga SHS, Gowrie SHTS, Tumu SHTS, Ullo SHTS, Denyaseman Catholic SHS Poano, Ourlady of Mercy SHS, Presbyterian SHS Tema, Obiri Yeboah SHTS, St. John's Integrated SHS, Wa SHS, and Bawku SHS. Three of these schools are from category A, 11 schools are from category B, and 30 schools are from category C.

As discussed in the "The Benchmarks" section, certain schools, such as Diaso SHS and Ejisu SHTS, may serve as benchmarks for others, providing valuable examples of best practices. Exploring these schools in detail could offer opportunities for knowledge transfer, fostering innovation in educational practices that improve overall performance, not only for the underperforming schools in this study but also for other institutions facing similar challenges.

Concluding Remarks and Policy Recommendations

Overall, the findings in this study highlight significant potential for enhancing the efficiency and effectiveness of senior high schools in Ghana, as significant variability in school performance was observed across the three performance criteria analyzed. Based on these findings, substantial benefits could arise from fostering knowledge exchange between high-performing and underperforming schools, promoting systemic innovation in educational practices. This aligns with a comprehensive approach to education reform that operates across macro-, meso-, and microlevels of analysis:

At the macrolevel, the findings contribute to systemic improvements in Ghana's education sector, a critical factor in driving broader economic development. By addressing the efficiency and effectiveness of schools across the nation, this study supports the goal of building an education system that fosters national growth and development.

At the mesolevel, the study focuses on improving organizational performance at the institutional level, specifically within senior high schools. By identifying key performance gaps and recommending strategies for knowledge sharing and benchmarking, the study emphasizes the importance of enhancing institutional processes to support school-wide improvements.

At the microlevel, the study underscores the potential for better resource allocation and management practices to improve individual student outcomes. By setting realistic performance targets and fostering peer learning, schools can create environments that facilitate student success, enhancing the quality of education on an individual level.

Specifically, a post-evaluation analysis of the processes at Diaso SHS and Ejisu SHTS is highly recommended, as these schools serve as strong benchmarks. Their practices could provide valuable learning opportunities for other schools, influencing organizational practices at the mesolevel while benefiting individual students at the microlevel.

Other policy recommendations stemming from our results with potential to improve the broader education system include the following:

First, for senior high schools with below-average performance scores across all dimensions, specific targets should be set to help them, in the initial phase, reach at least the level of average performers. This approach would facilitate gradual improvement in their performance without setting overly ambitious targets that may be perceived as unachievable. For other underperforming schools, targets could be based on the sector's best practices.

Second, top-performing schools should be encouraged to share their knowledge and practices with underperforming schools. This peer learning process can drive systemic improvements, leveraging existing innovation within the education sector.

Third, an observatory should be established to monitor the annual performance of senior high schools nationwide. This observatory would have the authority to intervene and implement improvements when necessary. If the establishment of such an observatory is not feasible in the short term, we recommend providing the current institutions responsible for supervising school performance with the necessary resources to effectively fulfill their mandate.

Fourth, we propose that the data collected by the observatory be made available to policymakers and researchers. This would allow the efficiency and effectiveness scores of each school to serve as benchmarks for all senior high schools at both regional and national levels and encourage further research on the performance of the schools.

Finally, there should be an appropriate reallocation of resources to improve the efficiency and effectiveness of underperforming schools. Ideally, all stakeholders in the education sector should collaborate on this effort, creating a knowledge-sharing ecosystem with potential to benefit all levels of the education system.

Although the findings of this research are robust and provide valuable insights for researchers, practitioners, and policymakers, this study has some important limitations.

The first limitation relates to the methodological constraints inherent in the DEA technique. It is well known that DEA evaluates relative rather than absolute performance. This means that the results obtained in this study are valid for the five Ghanaian regions and the 215 schools analyzed but should not be generalized to schools and regions outside this scope. Nonetheless, it is important to highlight that the methodology and models we propose for assessing the efficiency and effectiveness of SHS have the potential to be applied to other regions in Ghana and even to other countries, thereby informing policy decisions at both national and international levels.

The second limitation stems from the fact that the study is based on data from the 2020 academic year, meaning that some findings may not fully reflect the current performance of the assessed schools. Future research can address this limitation by applying the proposed models to more recent data and extending the analysis to all schools in the country.

Finally, due to data unavailability, this study was unable to incorporate key student-related factors—such as family income, parental education level, and employment status—that could influence school performance. In light of the diverse backgrounds of students in secondary/high schools, some authors have suggested the importance of including environmental or external variables in school performance evaluations (Agasisti & Zoido, 2019; Minuci et al., 2019). However, our study highlights the importance of considering students' entry grades and the hierarchical classification of schools to ensure a fair performance assessment. By incorporating these factors, the performance targets set for underperforming schools through benchmarking are more likely to be achievable, positively impacting both individual and institutional outcomes.

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Data Availability Data will be made available upon request to the corresponding author.

Declarations

Ethics Approval This research does not require ethical approval as it relies on secondary data from publicly available sources and does not use any human or animal subjects.

Conflict of interest The authors declare no competing interests.

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