BMC Health Services Research

RESEARCH

Open Access

Technical efficiency analysis of advanced medical centers in Burkina Faso

Pauline Kergall[1,2*], Marlène Guillon[1,3] and Jacky Mathonnat[3,4]

Abstract

Introduction Burkina Faso faces many challenges in the health domain, with no real opportunity for an increase in public health expenditures. In Burkina Faso, as in all low-income countries, health spending efficiency is crucial. The objective of this paper is to assess the efficiency of Advanced Medical Centers (AMCs)—which correspond to district hospitals—in Burkina Faso over the 2017–2020 period and identify the factors that promote—or, on the contrary, limit—the efficiency of these health structures.

Method We first assessed the efficiency level of the 45 AMCs running in the country between 2017 and 2020 using a bootstrap Data Envelopment Analysis (DEA) methodology. Inputs include the number of doctors, nurses, other medical staff, non-medical staff, and beds, while output variables correspond to the number of inpatients, surgeries, outpatients, and inpatient days. In a second step, determinants of AMC's efficiency levels were explored using a double-bootstrap procedure. The roles of AMCs' internal and environmental factors were both considered.

Results We found a mean efficiency score of 0.51 over the study period, indicating that AMCs could have almost doubled their healthcare production without needing additional resources. The size, education level, and health status of the covered population and the density of the healthcare supply in the district appeared to be the driving factors of AMCs' efficiency.

Conclusion Our results indicate that improving the efficiency of AMCs should be a high-level priority for the Burkinabe health policy. Resources could be reallocated across AMCs to increase the overall efficiency of the health system.

Key messages

- The efficiency of health spending is of crucial importance in Sub-Saharan Africa, given the important health needs and financial constraints those countries face.
- No recent study has investigated the efficiency of Advanced Medical Centers (AMCs), which correspond to district hospitals, in Burkina Faso, although they play a pivotal role in the health system.
- The healthcare production of AMCs could have almost doubled over the 2017–2020 period without any increase in the resources used.
- Resource reallocation across AMCs based on population size and health needs could be performed to increase the overall efficiency of the health system.

*Correspondence:
Pauline Kergall
kergall@unistra.fr

Full list of author information is available at the end of the article

Keywords Efficiency, Healthcare, Hospitals, Burkina Faso

Introduction

Context

Burkina Faso, like most sub-Saharan African countries, faces a worrying health situation, with considerable unmet health needs and a long way to go to achieve universal health coverage (UHC), despite important progress made over the last decades. The population of Burkina Faso is very young, with two thirds of the population currently under 25 years old, according to UNICEF,[1] life expectancy only 59 years, [2] and worrying maternal mortality and morbidity indicators. Indeed, the maternal mortality ratio (MMR) is 320 per 100,000 births, while the average for low- and middle-income countries (LMICs) is 231 and the sustainable development goal (SDG) 3 target is 70 by 2030.[3] The under-5 mortality rate is 85 per 1,000 births, far above the average of 40 among LMICs. In addition, Burkina Faso ranks 182nd out of 189 countries for the Human Development Index. Burkina Faso is ranked as a low-income country, according to the World Bank definition. The economy is still mainly based on agriculture, with more than 70% of the population living in rural areas. Macroeconomic conditions are worrying despite the rebound in growth observed in 2021 and 2022, which is important but considered fragile [1]. The overall fiscal deficit, including grants, which averaged 3.3% of GDP over the 2011–19 period, rose to 10.4% in 2022 and is estimated at 7.8% for 2023; over the same period, public debt rose from 30.3% of GDP to 54.3% in 2022 and is expected to reach 60% in 2024 [2]. Then, despite huge health needs and chronic underfunding of the health system, it would be a tricky challenge to envision a substantial and sustainable increase in public financing for health in the short and medium term in Burkina Faso, especially as health is in competition with other sectors, in particular security expenditures.

In addition to these challenges, insecurity issues have appeared in recent years with the presence of terrorist groups in the northern part of the country leading to the closing of healthcare facilities for prolonged periods. Indeed, as of the end of December 2019, according to a report from the Ministry of Health [3], 96 health facilities were recorded as closed, accounting for 8.5% of the health facilities in six regions affected by insecurity. Additionally, 133 facilities, representing 11.6% of facilities in those six regions, reduced their services, meaning no advanced vaccination or night shifts. This is estimated to have deprived more than 1.2 million people of access to healthcare due to this malfunctioning of healthcare facilities. Moreover, the country has been facing political instability in recent years, making medium-term policy planning more difficult. According to worldwide governance indicators, the index of political stability and absence of violence, which is measured on a scale from −2.5 to 2.5, where 2.5 represents the best political governance, decreased from −0.1 in 2010 to -1.5 in 2020, indicating a serious deterioration of the political situation over the period, especially between 2018 (-1) and 2020 (-1.5).[4] In view of these severe constraints, the need to make the best use of the resources currently allocated to the health system is critical, and improving efficiency is becoming of paramount importance for health policy in Burkina Faso. In a generic sense, *efficiency* reflects the relationship between the resources used (inputs) and the results obtained (outputs), whatever they may be. Improving efficiency means obtaining the same results with fewer resources or obtaining more results with the same amount of resources. In the first case, it is necessary to ensure that efficiency gains are reallocated within the health sector so that they do not result in an actual decrease in the budget allocated to this sector [4]. This study focuses on the technical efficiency of advanced medical centers (AMCs), which correspond to district hospitals, in Burkina Faso. AMCs were selected because of the pivotal function they serve in the Burkinabe healthcare system and their fundamental role in progressing toward the health SDGs. In Burkina Faso, the public healthcare system is organized following a common three-level healthcare pyramid (see Figure A, Appendix 1) [5]. The first level of care includes two layers: the first layer, which comprising medical centers (MCs), health and social promotion centers (HSPCs), and isolated dispensaries and maternity wards; and the second layer, which comprises medical centers with a surgical branch (called AMCs). AMCs are the reference structures for the first-layer health facilities of the first level of care. The first layer of the first level of care—i.e. the HSPCs and the MCs—provides a minimum package of activities (MPA) that includes the diagnosis and treatment of common conditions, prenatal and postnatal consultations, the monitoring of children, deliveries, vaccinations, and family planning. The second layer of the first level of care, the AMCs, complements the first layer by providing a complementary package of activities (CPA). AMCs' missions include taking charge of cases referred by the first-layer health facilities and handling

[1] https://www.unicef.org/media/100531/file/Burkina-Faso-2020-COAR.pdf.

[2] https://donnees.banquemondiale.org/indicator/SP.DYN.LE00.IN?locations=BF.

[3] https://www.un.org/sustainabledevelopment/health/.

[4] https://databank.worldbank.org/source/worldwide-governance-indicators.

medical, surgical, and obstetrical emergencies but also comprise hospitalizations; laboratory and medical imaging activities; counter-referrals; referrals to the regional or university hospitals; and the collection, processing, and analysis of health information. Studying the efficiency of AMCs, which provide care for the most common infectious, chronic, maternal, and infantile diseases at the first level of the healthcare system, is crucial to better understanding the weaknesses and strengths of the Burkinabe health system and improving the healthcare supply for the population.

Our objective was to assess the technical efficiency of AMCs throughout the whole territory of Burkina Faso over the 2017–2020 period and identify the factors that foster, or limit, the efficiency of these health structures. The efficiency of healthcare structures has already been studied in various Sub-Saharan countries, such as Ghana [6], Côte d'Ivoire [7], Kenya and Eritrea [8, 9], Botswana [10], and Zimbabwe [11]. To the best of our knowledge, however, no recent study has explored the efficiency of healthcare structures in Burkina Faso. The only studies available for Burkina Faso, published in 2009 [12] and 2011 [13], focused on the basic health structures constituting the first layer of the first level of the healthcare system (i.e., HSPCs). Our article concerns AMCs, which are positioned above HSPCs. HCSPs and AMCs, therefore, play different roles in the sanitary pyramid and have different missions. Moreover, the studies mentioned above focused exclusively on the district of Nouna, whereas our study has national coverage. In the first step of our analysis, bias-corrected efficiency scores of AMCs were calculated using data extracted from the national health information system. In a second step, to identify policy implications for the reallocation of resources within the healthcare system to boost its overall efficiency, a double-bootstrap procedure [14] was used to estimate the factors associated with AMCs' efficiency. Thus, not only do we use more recent data, allowing for up-to-date information on the performance of the Burkinabe health system to design new policies, but we also offer a broader perspective of the situation. Additionally, our methodology differs from that of Marschall and Flessa (2009, 2011). Indeed, their 2009 study did not use Simar and Wilson's double-bootstrap methodology, while their 2011 study used bootstrap only in the second step of the procedure to estimate the driving factors of efficiency. The variables selected as inputs and outputs in DEA also differ in our study, given the differences in the health structures considered. The study is organized as follows. Section 2 details the methods and data used to estimate both the efficiency scores and the factors associated with those scores. The results are displayed in Section 3 and discussed in Section 4.

Data and method

Efficiency analysis

Method

The efficiency of health facilities can be assessed using two orientations: an input orientation and an output orientation. In an *input orientation*, technical efficiency reflects the capacity of a health facility to minimize the use of inputs to achieve a given level of healthcare production. In an *output orientation*, technical efficiency reflects the capacity of a healthcare facility to obtain a maximum level of care production (of a given quality) from a given set of inputs. An output orientation was chosen to measure the efficiency of AMCs because of the existence of unmet health needs in Burkina Faso and the impossibility of an increase in health expenditure in the near future due to the severe economic constraints on health financing.

Measuring technical efficiency is a two-step process. The first step consists of estimating a production frontier (efficiency frontier) representing the maximum amount of output (healthcare production) achievable for different levels of input use (resources used by the selected health facilities: i.e., the AMCs). The second step consists of calculating the efficiency score of each AMC as its distance from the frontier: i.e., the difference between the actual healthcare production of an AMC and the maximum production achievable if it were perfectly efficient (i.e., located on the efficiency frontier). Efficiency can be measured with two different methodologies: a parametric one using Stochastic Frontier Analysis [15] and a non-parametric one, which includes several methods, such as the Data Envelopment Analysis (DEA) [16, 17] or the Free Disposal Hull (FDH) [18], among others. In the parametric methodology, a hypothesis on the form of production function must be formed. Since there is a high degree of uncertainty about the production process of healthcare facilities, especially regarding the substitutability/complementarity relationships between capital and labor or between the different types of human resources, we used a nonparametric approach to measure the efficiency of AMCs. In addition, the non-parametric approach, unlike the parametric one, allows for the use of multiple inputs and outputs, which is essential to best represent the diversity of missions provided and resources used by AMCs.

Within the non-parametric approach, we chose to use the DEA approach which is the most commonly used in the literature assessing the efficiency of healthcare facilities in sub-Saharan Africa [19] or more globally [20, 21]. Statistical inference for DEA estimates can be obtained by using bootstrapping that allows to estimate the sampling bias and the confidence interval of the original estimate and to produce bias-corrected efficiency scores [22]. After testing for the appropriate bootstrap procedure to apply, we estimate bias-adjusted efficiency scores for AMCs using homogeneous bootstrap with 1,000 replications and under the hypothesis of varying returns to scale. As the assumption of constant returns to scale implies an optimal size for healthcare facilities, variable returns to scale were preferred to better reflect the reality of the healthcare system organization and to measure technical efficiency independently of scale economies. In addition, as DEA estimations are sensitive to outliers, a robustness check was conducted using a leave-one-out analysis [23]. Estimations were conducted using Stata®, version 16 (StataCorp LLC, College Station, TX).

Input and output data

To measure the efficiency of AMCs, the main resources available to them should be considered as inputs and the activities that reflect their main functions should be included as outputs. As the number of inputs and outputs increases, however, a corresponding rise in the number of observations needed for score calculation was observed. Hence, it was advisable to select only the most pertinent input and output variables for analysis. This selection was made based on the literature and discussion with local authorities.

According to Babalola and Moodley [19], the inputs most often used in the literature to measure the efficiency of health facilities in Sub-Saharan countries include staff resources (medical and non-medical), financial resources (operating expenses, drug expenditures), data on the size of facilities (number of beds), and functional equipment when the information is available. The most frequently used outputs are variables related to outpatient consultations, hospitalizations (number of hospitalizations or inpatient days), maternal and child health (prenatal consultations, deliveries, postnatal consultations, child vaccinations), and surgeries or health education, depending on the level of the facilities considered and the context in which they operate.

In this study, five input variables were selected: the number of doctors, nurses, other medical staff, non-medical staff, and beds. The number of doctors includes doctors from all specialties working in the AMC. The number of nurses covers both registered nurses and state-certified nurses. Other medical staff includes pharmacists, midwives, certified birth attendants, auxiliary birth attendants, laboratory/biology technicians, radiology technicians, and pharmacy technicians. The number of non-medical staff includes sanitary technicians, ward boys/girls, hospital executive assistants, hospital and health-service managers, and hospital and health-service administrators. Lastly, the number of beds corresponds to the total of beds available in all wards, including maternity and post-delivery services. Four main output variables were selected: the number of inpatients, surgeries, outpatients, and inpatient days. The number of inpatient days and outpatients were available in total and disaggregated by age categories (<5 years, 5–14 years, and >15 years). The number of surgeries includes both planned and emergency surgeries. For all outputs, the means per trimester, rather than annual values, were calculated to allow for the inclusion of hospitals with missing values.

Three sources were used to collect data on inputs and outputs: 1) the health information system (HIS) and published health and education statistical yearbooks; 2) existing but unpublished data available upon authorization from the Ministry of Health; and 3) specific data collected through a questionnaire sent to all AMCs (Appendix 2). The detailed source of each variable is available in Appendix 3. Based on the literature, a poll of candidate variables was created before reaching final selection after discussions with local health authorities. Data were collected for all public AMCs in the country. The choice of input and output variables was constrained by the availability of data and by quality issues. For example, it was not possible to include data on medical imagery or biology tests as outputs because they were not recorded by all the AMCs. In addition, the year 2019 was marked by various large-scale events in the country. First, a major strike of healthcare workers prevented the recording and correct reporting of HIS data. Second, insecurity-related problems (terrorism and intercommunity conflicts) led to the closure or reduced operation of some AMCs for repeated prolonged periods. As a result, the year 2019 was be excluded from the analysis. The study period, therefore, includes years 2017, 2018, and 2020.

Efficiency models

Since the DEA method is sensitive to the number of input and output variables selected, and to ensure the robustness of the results, five robustness models were estimated in addition to the main model. The main model includes the number of doctors, nurses, and beds as inputs and the number of inpatients, outpatients, and surgeries as outputs. Details on the inputs and outputs used in the six models estimated can be found in Table A, Appendix 4.

Factors associated with efficiency

Method

The use of two-stage models, where efficiency scores are first calculated and then regressed on a set of explanatory variables, to study the factors associated with efficiency has been challenged in the literature because efficiency scores calculated in the first step are not observations but rather estimates of true efficiency [14]. Moreover, as efficiency scores calculated through non-parametric approaches are relative, and then dependent on each other, they may be considered as serially correlated [14]. Thus, we used the double-bootstrap procedure proposed by Simar and Wilson [14] to obtain a valid inference for the regression of efficiency scores on a set of explanatory variables. In this procedure, unbiased DEA scores were first computed by subtracting the sampling bias computed through a first bootstrap from the initial estimates of the scores. The unbiased scores were then regressed on a set of explanatory variables using a bootstrapped, truncated regression that produces unbiased estimators and confidence intervals.

Explanatory variable data

Two categories of factors influencing the efficiency of AMCs could be identified: internal and environmental factors. Internal factors are characteristics specific to AMCs that they (or health authorities) can modify, while environmental factors do not depend directly on AMCs: for example, the geographical environment in which they operate. The choice of explanatory variables used to estimate the factors influencing AMCs' efficiency was limited by the availability of data. For example, it was not possible to include the age of the hospital or patient satisfaction in our analysis. Furthermore, the relatively small number of observations (45 AMCs over three years) restricted the number of explanatory variables that could be used in the regression analyses. Given these constraints, the selection of candidate explanatory variables was made based on discussions with local health authorities and after carefully reviewing previous efficiency studies on similar health structures. Table 1 describes the retained variables and our hypotheses regarding their effect on AMCs' efficiency level. More details on those variables are available in Appendix 5..

Regression specifications

Eight regression models, combining the variables identified as potential efficiency determinants, were estimated (Table 2). All regressions were run using the inputs and outputs described in Model 1 (see Sect. 2.1.3).

Regression 1 includes the following variables: population size, lower secondary education completion rate, malaria incidence, number of health facilities below the AMC level per 10,000 inhabitants, share of doctors among AMC's medical staff, and a categorical variable for the year. In regressions 2 and 3, the higher secondary education completion rate (regression 2) and secondary education enrollment rate (regression 3) were used as alternative measures of educational attainment. In regression 4, the urbanization rate was introduced in place of educational attainment (the two measures being highly correlated; see Table B, Appendix 5). In regressions 5 and 6, the measure of healthcare supply density was changed for the number of nurses per 10,000 inhabitants (regression 5) and for the existence of an MC in the district (regression 6). In regression 7, the share of doctors among AMCs' medical staff was replaced by the number of nurses per doctor. Regression 8 added the poverty rate[5] and the number of violent events to regression 1.

Results

Descriptive statistics

Descriptive statistics for inputs and outputs of the 129 observations for which an efficiency score was calculated are displayed in Table 3. On average, 9.12 doctors and 54.40 nurses operated in each AMC. The mean number of beds available was 70.87. Per trimester, the average number of inpatients in each AMC was 985, while the average number of outpatient visits was 4,068. The mean number of surgeries per trimester was 123..

Table 3 also presents the descriptive statistics of the explanatory variables for the 123 observations used in regression 1. The mean district population size was 308,000 inhabitants. About a third (32.39%) of districts' children had completed lower secondary education. The mean incidence rate of malaria per 1,000 inhabitants was 578.64 in the districts studied. The average number of healthcare centers at the first layer of the first level per 10,000 inhabitants was 1.29. On average, doctors represented 6.71% of AMCs' medical staff, and medical staff accounted for 88.41% of AMCs' total staff.

Efficiency scores

The scores of the six models were highly correlated (Table C, Appendix 6). Indeed, all rank-correlations (Spearman correlations) were significant at the 1% level and ranged between 0.81 (between models 3 and 5) and 0.99 (between models 2 and 3). This high correlation among our six models indicates a good robustness of the efficiency scores calculated. The scores presented in the following sections are those of Model 1, but bias-adjusted scores for all six models are available in Table D, Appendix 7.

AMCs' bias-adjusted efficiency scores ranged from 0.19 to 0.85 over the study period (2017–2020), with an overall average of 0.51. This means that, on average, AMCs could have almost doubled their healthcare production (+96% with stable resources). Figure 1 presents the detailed distribution of efficiency scores in our sample. Details by regions can be found in Table E, Appendix 8..

Examining the evolution over time, the mean efficiency scores were 0.52, 0.53, and 0.47 in 2017, 2018, and 2020, respectively (Table F, Appendix 9). The decreasing trend observed between 2018 and 2020 was significant at the 10% level (t=0.9189 and p=0.0582). Details of the yearly

[5] The poverty rate was available only at the regional level; thus, it was not included in the first specification.

Table 1 Hypotheses on the effect of variables influencing efficiency

	Variable	Effect on efficiency	Hypotheses
Internal variables	Share of doctors among medical staff	+/-	+ Supported by other medical staff, doctors are able to treat a broader spectrum of diseases, which increases the activity and efficiency of AMCs with proportionally more doctors. Reputation effect: AMCs with more doctors are likely more attractive to patients. - A greater number of doctors could lead to a decrease in the number of revisits and re-hospitalizations through a "quality-of-care" effect and therefore lead to a decrease in the level of activity and efficiency of AMCs. A high proportion of doctors could be a sign of low task-shifting, reducing AMCs' efficiency.
	Nurses per doctor	+/-	+ A high number of nurses per doctor could be a sign of high task-shifting, increasing AMCs' efficiency. - A low proportion of nurses per doctor could be a sign of low task-shifting, reducing AMCs' efficiency.
Environmental variables	Population size	+	AMCs located in more populated districts might face greater demand.
	Urbanization rate	+	AMCs located in urban districts might face greater demand.
	Lower secondary education completion rate Higher secondary education completion rate Enrollment rate for secondary education[a]	+/-	+ Higher levels of education are associated with greater use of care in the case of illness. Thus, AMCs located in districts with a more educated population may face a greater healthcare demand, which stimulates their activity and efficiency. - A higher level of education in the population is associated with fewer risky behaviors and more preventive behaviors. AMCs located in districts with a more educated population could, therefore, face a lower healthcare demand that would reduce their activity and efficiency.
	Poverty rate	+/-	+ Poor populations are in poorer health and in more need of care. They seek care later, which leads to a worsening of their pathologies, which are more likely to be treated at the AMC level. - Poor populations are more likely to forego care because of comparatively high medical, travel, and opportunity costs. This could reduce the demand for care directed to the AMCs located in poor districts.
	Malaria incidence	+	This indicator was retained as a proxy for the health status of the population. The higher the incidence rate, the lower the health status of the population and the higher the healthcare demand might be.
	Insecurity	-	Higher levels of healthcare renunciation in insecure districts (limitations of traveling) and the part-time closure of AMCs in those districts could lead to a reduction in AMCs' activity and efficiency.
	Number of healthcare centers below AMCs in the district per 10,000 inhabitants Presence of a medical center in the district Number of nurses per 10,000 inhabitants	-	Access to basic care is easier in districts where the supply of primary care through first-layer, first-level health facilities is denser. This could result in a decrease in the activity of the AMCs through less self-referral and reduced disease complications.

[a] Lower secondary education completion rate, higher secondary education completion rate, and enrollment rate for secondary education are used as proxies for educational level

scores for each AMC are displayed in Table G, Appendix 10.

Factors associated with efficiency

The results of the double-bootstrap truncated regressions analyzing the factors associated with AMCs' efficiency levels are presented in Table 4.[6]

[6] To ensure the absence of multicollinearity bias, we calculated VIF scores for specification 1. The mean VIF was 1.43, with all VIF values lower than 2.5.

Population size was positively associated with AMCs' efficiency in all specifications. When introduced in specification 4, the urbanization rate was also positively associated with the efficiency of AMCs. These results imply that AMCs located in districts with a large and urban population tended to be more efficient over the study period. No matter what measure was used, education was always positively associated with AMCs' efficiency (specifications 1–3). In all regressions, a positive association was found between malaria incidence and AMCs' efficiency. On the other hand, the poverty rate and insecurity level were negatively but insignificantly associated

Table 2 Regressions models of factors influencing efficiency

	Regression specifications							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Population size (10,000s)	X	X	X	X	X	X	X	X
Urbanization rate				X				
Lower secondary education completion rate	X				X	X	X	X
Higher secondary education completion rate		X						
Enrolment rate for secondary education			X					
Poverty rate								X
Malaria incidence per 1,000 inhabitants	X	X	X	X	X	X	X	X
Insecurity								X
Number of healthcare centers below AMC in the district per 10,000 inhabitants	X	X	X	X			X	X
Number of nurses per 10,000 inhabitants					X			
Medical center in the district						X		
Share of doctors among medical staff	X	X	X	X	X	X		X
Nurses per doctor							X	
Years	X	X	X	X	X	X	X	X

with AMCs' efficiency. The density of healthcare facilities at the first layer of the first level in the district was negatively associated with AMCs' efficiency in all specifications. Still, the density of nurses per 10,000 inhabitants in the district (specification 5) and the presence of at least one MC in the district (specification 6) did not reach significance. Having a medical staff largely composed of doctors seemed to decrease the efficiency of AMCs, while the number of nurses per doctor was associated with AMCs' increased efficiency.

To assess the sensitivity of our results to the presence of outlier AMCs in the sample that could distort the production frontier and wrongly influence the regression results, we ran, in the spirit of partial frontier methodologies like order-alpha and order-m analyses [24], a leave-one-out analysis, as suggested by Simar (2003) [23]. The end goal of this analysis was to identify potential outlier AMCs and remove them from the sample before rerunning the double-bootstrap truncated regression analysis. Appendix 11 details the methodology applied and the results obtained. We found that our regression results were robust to the removal of potential outlier AMCs, thus increasing confidence in our analysis and the discussion of its associated policy implications.

Discussion

The AMCs' efficiency scores obtained in our analysis (0.51 on average) appear relatively low compared to the scores obtained in the efficiency studies of health facilities conducted in similar countries using the DEA method. For example, in Ghana, a neighboring country of Burkina Faso, a study conducted at the district-hospital level found an average efficiency of 0.61 and efficiency scores ranging from 0.37 to 1 [6]. In Kenya and Eritrea, mean efficiency scores of 0.96 and 0.97 were found for district and secondary-level community hospitals, respectively [8, 9]. The lower scores obtained in our study are partly due to the use of a bootstrap methodology, which corrects for the problem of the overestimation of simple DEA scores due to sampling bias. Using a bootstrap procedure, the mean efficiency of district hospitals in Côte d'Ivoire in 2012 and 2013 was found to be 0.62 and 0.56, respectively, with extrema of 0.14 and 0.86 [7]. In a different context but using a similar methodology, a mean efficiency score of 0.55 was obtained for county-level maternal and child health hospitals in China [25]. Nevertheless, the overall low level of efficiency among AMCs found in our study indicates that there is substantial room to maneuver to increase the care provided to the population without a foreseen increase in AMCs' resources.

Regarding the factors associated with AMCs' efficiency levels, most of our results are in line with previous literature. Indeed, similar to our results, the size of the catchment population was also found to be positively associated with the efficiency of public district hospitals in Bangladesh [26], public health centers in Ethiopia [27], community health centers in Indonesia [28], public hospitals in Iran [29], and maternal and child health services in Ethiopia [30, 31]. Moreover, as in our study (specification 4), Achoki et al. [32] highlighted that healthcare structures located in urbanized districts were more efficient in Zambia. The positive association we found between the population size/urbanization rate and AMCs' efficiency might be linked to the fact that AMCs located in more populous and denser districts face greater healthcare demand, all else being equal, leading to higher efficiency.

The positive association between educational attainment and AMCs' efficiency obtained in our analysis is also in line with previous results in the literature. In a macroeconomic analysis of 172 countries, Jordi et al. [33]

Table 3 Descriptive statistics

	Mean	Standard deviation	Coefficient of variation
Inputs (N = 129)			
Doctors	9.12	7.80	0.86
Nurses	54.40	43.82	0.81
Other medical staff	29.55	26.37	0.89
Non-medical staff	13.78	5.11	0.37
Beds	70.87	23.37	0.33
Outputs (N = 129)			
Inpatients	984.69	419.38	0.43
Inpatients < 5 years	360.97	185.31	0.51
Inpatients 5–14 years	93.03	50.02	0.54
Inpatients > 15 years	530.69	298.40	0.56
Inpatient days	2,392.12	1,238.69	0
Surgeries	123.38	91.05	0.74
Outpatients	4,068.38	3,684.01	0.91
Outpatients < 5 years	1,450.13	1,736.08	1.20
Outpatients 5–14 years	430.90	500.34	1.16
Outpatients > 15 years	2,187.36	1,710.31	0.78
Explanatory variables (N = 123)			
Population size	308,038.8	151,671.5	0.49
Urbanization rate	19.16	19.88	1.04
Lower secondary education completion rate	32.39	16.37	0.51
Higher secondary education completion rate	17.00	8.93	0.53
Enrollment rate for secondary education	25.40	10.60	0.42
Poverty rate	44.67	15.61	0.35
Malaria incidence per 1,000 inhabitants	578.64	170.75	0.30
Insecurity	6.55	31.06	–4.74
Number of healthcare centers below AMC in the district per 10,000 inhabitants	1.29	0.35	0.27
Number of nurses per 10,000 inhabitants	3.11	1.01	0.33
Medical center in the district	0.53	0.50	-0.95
Nurses per doctor	6.49	4.16	0.64
Share of medical staff among total staff	88.41	5.10	0.06

found that more years of schooling was associated with greater technical efficiency in converting health spending to UHC goals. In a study investigating the efficiency of maternal and child health services in Zambia, a higher proportion of educated women in the district was found to be positively associated with efficiency [32]. The positive association between the population's education level, measured here with the proxy of children's school attendance, and AMCs' efficiency is likely related to differences in care-seeking behaviors based on patients' education level [34]. A higher level of education is associated with greater use of care in the event of illness, which leads AMCs in districts with higher education levels to face a greater demand for care, in turn increasing their activity and efficiency.

The positive effect of malaria incidence on AMCs' efficiency also appears consistent with the previous literature. The health status of the population can be measured using several proxies depending on the main challenges faced by a country and the epidemiological profile of the population. In Côte d'Ivoire, the prevalence of HIV and tuberculosis co-infection among the population was found to be positively associated with district hospitals' efficiency [7]. In Kenya, higher HIV prevalence was positively associated with the efficiency of health systems at the county level [35]. A population with higher malaria incidence or HIV burden presents a lower health status and exhibits higher healthcare needs, resulting in higher healthcare demand and efficiency for health structures. It would, therefore, make sense to reallocate some of the efficiency gains to highly malaria-affected areas while also ensuring that internationally validated malaria-control strategies are effectively implemented there.

We found that the density of the lower-layer healthcare supply in the covered area was negatively associated with AMCs' efficiency. This indicates that AMCs located in districts where the supply of the first layer of the first level of care is denser tend to be less efficient. This could mean that the first layer of care formed by the HSPCs and MCs drains a substantial part of the demand regarding the basic health needs of the population in Burkina Faso, in line with their role in the healthcare pyramid, thus limiting direct access and unjustified referrals to AMCs, which reduces their activity and efficiency. This result is consistent with a previous study conducted in Palestine that found that the efficiency of public hospitals was negatively correlated with the number of primary-care centers available per 10,000 inhabitants in the governorate [36]. By contrast, a Chinese study found a positive association between the number of village health posts per 10,000 households and the efficiency of municipal hospitals [37].

We did not find a significant negative association between poverty and AMCs' efficiency. This finding might initially be seen as counterintuitive since the literature on LMICs has already extensively documented the negative effect of poverty on the efficiency of health facilities [28, 38, 39]. The lack of significance of the poverty rate in our study might be explained by the fact that poverty was only measured at the regional level, not the district level, and was constant over the period studied. Thus, our indicator lacked precision and could not fully capture the heterogeneity of poverty levels across districts and their effect on AMCs' efficiency. Another counterintuitive result is the lack of a significant association between insecurity and AMCs' efficiency. One

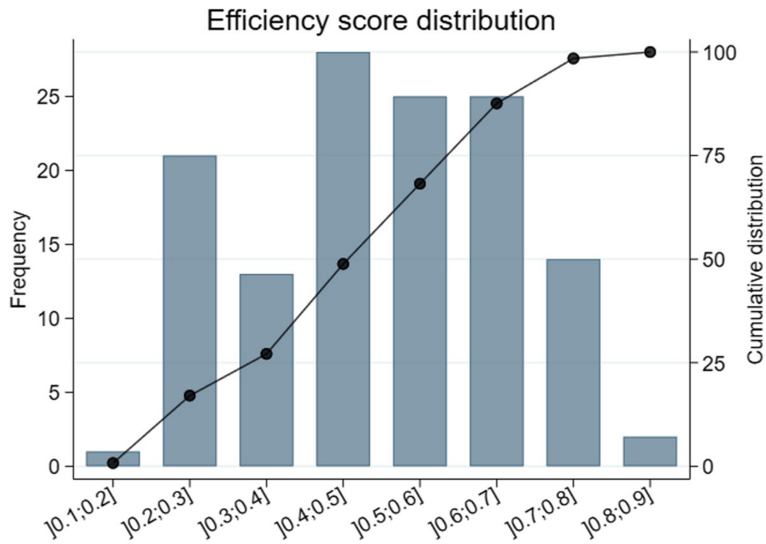

Fig. 1 Efficiency score distribution

explanation could be that the AMCs located in districts where insecurity is high are also those with a high malaria incidence and a low education rate.

Regarding internal factors, the negative association we found between the share of doctors in medical staff and AMCs' efficiency differs from the main results of the literature. Indeed, Guillon et al. [40] found a positive association between the share of doctors among medical staff and the efficiency of first-level rural health centers in Mongolia, while Jing et al. [41] reported a positive association between the ratio of doctors to nurses and the efficiency of public and private hospitals in China. In Ghana, a positive association was also found between the proportion of qualified staff among total staff and hospitals' efficiency [42]. One study conducted in Iran, however, highlighted conclusions in line with our results. Kakemam and Dargahi [43] found a positive correlation between the number of nurses per doctor and the efficiency of public hospitals in Iran, meaning that the lower the share of doctors, the higher the efficiency of hospitals. The negative association we found between the share of doctors among medical staff and AMCs' efficiency could be explained by a "quality effect" if the care provided by doctors was more effective than that provided by other health staff and led to a reduction in the number of return visits and re-hospitalizations. It is also possible that a higher share of doctors reduces AMCs' efficiency by decreasing task-shifting or by limiting AMCs' financial ability to hire other productive medical staff, given the relatively high salaries of doctors. The positive association found between the number of nurses per doctor and the efficiency levels seems to confirm that higher task-shifting could increase AMCs' efficiency.

Three main implications for Burkina Faso's health policy emerge from the study's findings. *First, improving the efficiency of AMCs should be a high-level priority in health policy.* With large heterogeneity across the sampled health facilities, we found that, on average, AMCs could have almost doubled their healthcare production with no additional resources over the study period. This result is grounds for making the improvement of AMCs' efficiency a top priority in health policy, as their financing is drastically insufficient for their needs and highly constrained by the macroeconomic and budgetary situation in Burkina Faso. *Second, the distribution of health personnel among AMCs should be reconsidered.* Our results indicate that resources could be relocated to more populous districts and districts with a lower density of healthcare supply and poor population health, where health needs are higher, to increase the overall efficiency of the Burkinabe health system. That said, it should be noted that it may be entirely justified to reduce the number of very inefficient AMCs if it is not possible to go below a certain level of resources to maintain the continuity of care. This could be a form of subsidy grounded on an equity criterion, mainly for low-efficiency AMCs that operate in particularly high-needs areas. Additional investigations supported by a solid knowledge of local specificities are required in all cases. *Third, tackling the issue of effective and robust verification of AMCs' resource and activity data.* The study highlighted several issues regarding the quality of the data collected at the health-facility level in Burkina Faso. This stresses the need for Burkinabe health authorities to better monitor their health-information system by, among other possible actions, integrating systematic verifications of activity data reported by health facilities. This problem distorts reality and hinders the relevant decision-making. This problem is not specific to the Burkinabe context, however, and health-data quality

Table 4 Results of factors associated with efficiency levels

	Specification							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Population size (10,000s)	0.0023* (0.0009)	0.0026* (0.0009)	0.0030** (0.0009)	0.0018† (0.0010)	0.0038*** (0.0011)	0.0035* (0.0014)	0.0017† (0.0009)	0.0019* (0.0010)
Urbanization rate				0.0028*** (0.0007)				
Lower secondary education completion rate	0.0048*** (0.0009)				0.0027** (0.0009)	0.0026** (0.0009)	0.0049*** (0.0009)	0.0037** (0.0011)
Higher secondary education completion rate		0.0060*** (0.0016)						
Enrolment rate for secondary education			0.0075*** (0.0015)					
Poverty rate								-0.0013 (0.0010)
Malaria incidence per 1,000 inhabitants	0.0006*** (0.0001)	0.0005*** (0.0001)	0.0005*** (0.0001)	0.0006*** (0.0001)	0.0005*** (0.0001)	0.0005*** (0.0001)	0.0006*** (0.0001)	0.0006*** (0.0001)
Insecurity								-0.0006 (0.0006)
Number of healthcare centers < AMC in the district per 10,000 inhabitants	-0.1975*** (0.0445)	-0.1321** (0.0409)	-0.1930*** (0.0424)	-0.1067* (0.0369)			-0.1740*** (0.0412)	-0.1948*** (0.0436)
Number of nurses per 10,000 inhabitants					-0.0016 (0.0152)			
Medical center in the district						0.0037 (0.0135)		
% of doctors among medical staff in AMC	-0.0094* (0.0038)	-0.0093* (0.0038)	-0.0104** (0.0040)	-0.0100** (0.0038)	-0.0109* (0.0042)	-0.0103* (0.0043)		-0.0096* (0.0040)
Nurses per doctor							0.0057* (0.0027)	
Year 2018 (Ref: 2017)	0.0522† (0.0304)	0.0460 (0.0302)	0.0397 (0.0296)	0.0314 (0.0295)	0.0337 (0.0316)	0.0402 (0.0316)	0.0416 (0.0285)	0.0550† (0.0299)
Year 2020 (Ref: 2017)	0.0290 (0.0317)	0.0156 (0.0309)	-0.0023 (0.0306)	0.0167 (0.0301)	0.0009 (0.0321)	-0.0045 (0.0328)	0.0019 (0.0290)	0.0327 (0.0313)
Constant	0.2045* (0.0828)	0.2000* (0.0842)	0.2251** (0.0818)	0.2376** (0.0870)	0.0723 (0.0908)	0.0589 (0.0890)	0.1307 (0.0745)	0.3369** (0.1207)
Observations	123	120	122	121	122	123	120	122

† $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$; standard errors in parentheses

was previously identified as a challenge in various LMICs [44–46].

Our study has some limitations. First, we cannot measure quality of care in AMCs given the lack of routine data collection in this area. This might be problematic for the measurement and comparison of AMCs' efficiency if quality of care is heterogeneous across the studied health facilities. Second, the data on various inputs and outputs and explanatory factors could not be integrated into the analysis due to either a lack of data or its low quality. This is, for example, the case for inputs and outputs related to medical imagery or biology tests or for precise measures (i.e., at the district level) of a population's poverty or education levels. It is also important to bear in mind that the associations found for factors influencing efficiency are correlational and not causal. Despite these limitations, our study sheds light on the important issue of low AMC efficiency and provides policy recommendations to improve this critical issue.

Conclusion

Previous studies on health efficiency in Burkina Faso focused primarily on lower-level structures, whereas this study concentrates on AMCs across the entire country with a different methodology. AMCs play a fundamental role in the Burkinabe healthcare system and in progressing toward the health SDGs, making their efficiency critically important. The results show that there is room for improvement in the efficiency of district hospitals in Burkina Faso. Even without additional investment, healthcare production could be enhanced. Among other solutions, reconsidering the distribution of health personnel based on districts' health needs and population sizes could be a way to improve the efficiency of AMCs, as well as focusing on areas where health needs are the most significant. Our study also underlines the need for intersectoral collaboration in shaping and implementing public policies to address both supply and demand factors effectively.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12913-024-11688-4.

Supplementary Material 1.

Acknowledgements
A preliminary version of the study was presented at an internal seminar in April 2022 at the Burkina Faso Ministry of Health, attended by directors of central services, regional health directors, and directors of AMCs. The authors thank the participants for their comments and suggestions, but remain solely responsible for the analyses and conclusions presented in this article.

Authors' contributions
P.K., M.G., J.M. conceived and designed the analysis. P.K., M.G., J.M. collected the data. P.K. and M.G. carried out the calculations. P.K., M.G., and J.M. performed the analysis. P.K., M.G., J.M. wrote the paper.

Funding
This study was financed by the French Development Agency and conducted as part of a FERDI-French Development Agency applied research program on the effects of Covid-19 in Sub-Saharan Africa.

Data availability
Anonymized data can be made available upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
This study was financed by the French Development Agency and conducted as part of a FERDI-French Development Agency applied research program on the effects of Covid-19 in Sub-Saharan Africa.The authors received consultation fees personally for this study and declared no other conflict of interest.

Author details
[1]Present address: University of Montpellier, Montpellier Recherche en Economie, Avenue Raymond Dugrand, 34960 Cedex 2, Montpellier, France
[2]BETA, University of Strasbourg, Strasbourg, France
[3]FERDI (Fondation pour les Etudes et Recherches sur le Développement International - Foundation for Studies and Research on International Development), Clermont-Ferrand, France
[4]University Clermont Auvergne, Senior Fellow & FERDI (Fondation pour les Etudes et Recherches sur le Développement International - Foundation for Studies and Research on International Development), Clermont-Ferrand, France

Received: 1 December 2023 / Accepted: 30 September 2024
Published online: 11 October 2024

References

1. IMF. Regional Economic Outlook. Sub-saharan Africa: a new shock and little room to Maneuver. IMF; 2022.
2. IMF. Regional Economic Outlook. Sub-saharan Africa: the Big funding squeeze. IMF; 2023.
3. Health Cluster WHO. Bulletin N°03 Du Cluster Santé Décembre 2019 - Burkina Faso | ReliefWeb.; 2020. Accessed April 23, 2024. https://reliefweb.int/report/burkina-faso/bulletin-n-03-du-cluster-sant-d-cembre-2019.
4. Barroy H, Cylus J, Patcharanarumol W, Novignon J, Evetovits T, Gupta S. Do efficiency gains really translate into more budget for health? An assessment framework and country applications. Health Policy Plann. 2021;36(8):1307–15. https://doi.org/10.1093/heapol/czab040.
5. Ministère de la santé. Rapport de l'évaluation Finale Du Programme National de Développement Sanitaire 2011–2020.; 2020.
6. Jehu-Appiah C, Sekidde S, Adjuik M, et al. Ownership and technical efficiency of hospitals: evidence from Ghana using data envelopment analysis. Cost Eff Resour Alloc. 2014;12(1):9. https://doi.org/10.1186/1478-7547-12-9.
7. Tiehi TN. Technical Inefficiency of District Hospitals in Côte d'Ivoire: Measurement, Causes and Consequences. IJEF. 2020;12(9):35. https://doi.org/10.5539/ijef.v12n9p35.
8. Kirigia JM, Emrouznejad A, Sambo LG. Measurement of Technical Efficiency of Public hospitals in Kenya: using data Envelopment Analysis. J Med Syst. 2002;26(1):39–45. https://doi.org/10.1023/A:1013090804067.
9. Kirigia JM, Asbu EZ. Technical and scale efficiency of public community hospitals in Eritrea: an exploratory study. Health Econ Rev. 2013;3(1):6. https://doi.org/10.1186/2191-1991-3-6.
10. Tlotlego N, Nonvignon J, Sambo LG, Asbu EZ, Kirigia JM. Assessment of productivity of hospitals in Botswana: a DEA application. Int Arch Med. 2010;3(1):27. https://doi.org/10.1186/1755-7682-3-27.
11. Guillon M, Audibert M, Mathonnat J. Efficiency of district hospitals in Zimbabwe: Assessment, drivers and policy implications. Health Planning Management. 2022;37(1):271–80. https://doi.org/10.1002/hpm.3337.
12. Marschall P, Flessa S. Assessing the efficiency of rural health centres in Burkina Faso: an application of Data Envelopment Analysis. J Public Health. 2009;17(2):87–95. https://doi.org/10.1007/s10389-008-0225-6.
13. Marschall P, Flessa S. Efficiency of primary care in rural Burkina Faso. A two-stage DEA analysis. Health Econ Rev. 2011;1(1):5. https://doi.org/10.1186/2191-1991-1-5.
14. Simar L, Wilson PW. Estimation and inference in two-stage, semi-parametric models of production processes. J Econ. 2007;136(1):31–64. https://doi.org/10.1016/j.jeconom.2005.07.009.
15. Aigner D, Lovell CAK, Schmidt P. Formulation and estimation of stochastic frontier production function models. J Econ. 1977;6(1):21–37. https://doi.org/10.1016/0304-4076(77)90052-5.
16. Farrell MJ. The measurement of productive efficiency. J Royal Stat Soc Ser (General). 1957;120(3):253. https://doi.org/10.2307/2343100.
17. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res. 1978;2(6):429–44. https://doi.org/10.1016/0377-2217(78)90138-8.
18. Deprins D, Simar L, Tulkens H. Measuring labor-efficiency in Post offices. In: Chander P, Drèze J, Lovell CK, Mintz J, editors. Public Goods, Environmental externalities and Fiscal Competition. Springer US; 2006. pp. 285–309. https://doi.org/10.1007/978-0-387-25534-7_16.
19. Babalola TK, Moodley I. Assessing the efficiency of Health-Care facilities in Sub-saharan Africa: a systematic review. Health Serv Res Managerial Epidemiol. 2020;7:233339282091960. https://doi.org/10.1177/2333392820919604.
20. Hafidz F, Ensor T, Tubeuf S. Efficiency Measurement in Health Facilities: a systematic review in low- and Middle-Income Countries. Appl Health Econ Health Policy. 2018;16(4):465–80. https://doi.org/10.1007/s40258-018-0385-7.
21. Mbau R, Musiega A, Nyawira L, et al. Analysing the Efficiency of Health Systems: a systematic review of the literature. Appl Health Econ Health Policy. 2023;21(2):205–24. https://doi.org/10.1007/s40258-022-00785-2.
22. Simar L, Wilson PW. Statistical inference in nonparametric frontier models: recent developments and perspectives. In: The Measurement of Productive Efficiency and Productivity Growth.; 2008:421–521.
23. Simar L. Detecting outliers in Frontier models: a simple Approach. J Prod Anal. 2003;20(3):391–424. https://doi.org/10.1023/A:1027308001925.
24. Tauchmann H. Partial Frontier Efficiency Analysis. Stata J. 2012;12(3):461–78. https://doi.org/10.1177/1536867X1201200309.
25. Zhang T, Lu W, Tao H. Efficiency of health resource utilisation in primary-level maternal and child health hospitals in Shanxi Province, China: a

bootstrapping data envelopment analysis and truncated regression approach. BMC Health Serv Res. 2020;20(1):179. https://doi.org/10.1186/s12913-020-5032-y.

26. Ahmed S, Hasan MZ, Laokri S, et al. Technical efficiency of public district hospitals in Bangladesh: a data envelopment analysis. Cost Eff Resour Alloc. 2019;17(1):15. https://doi.org/10.1186/s12962-019-0183-6.
27. Bobo FT, Woldie M, Wordofa MA, et al. Technical efficiency of public health centers in three districts in Ethiopia: two-stage data envelopment analysis. BMC Res Notes. 2018;11(1):465. https://doi.org/10.1186/s13104-018-3580-6.
28. Miharti S, Wittek R, Los B, Heyse L, Community Health Center Efficiency. The impact of Organization Design and local context: the case of Indonesia. Int J Health Policy Manag Published Online April. 2021;13:1. https://doi.org/10.34172/ijhpm.2021.19.
29. Mohamadi E, Kiani MM, Olyaeemanesh A, et al. Two-step estimation of the Impact of Contextual Variables on Technical Efficiency of hospitals: the Case Study of Public hospitals in Iran. Front Public Health. 2022;9:785489. https://doi.org/10.3389/fpubh.2021.785489.
30. Yitbarek K, Abraham G, Adamu A, et al. Technical efficiency of neonatal health services in primary health care facilities of Southwest Ethiopia: a two-stage data envelopment analysis. Health Econ Rev. 2019;9(1):27. https://doi.org/10.1186/s13561-019-0245-7.
31. Yitbarek K, Adamu A, Tsega G, et al. Technical Efficiency of Maternal and Reproductive Health Services in Public Hospitals of Oromia Regional State, Ethiopia. Health Serv Insights. 2019;12:117863291983763. https://doi.org/10.1177/1178632919837630.
32. Achoki T, Hovels A, Masiye F, Lesego A, Leufkens H, Kinfu Y. Technical and scale efficiency in the delivery of child health services in Zambia: results from data envelopment analysis. BMJ Open. 2017;7(1):e012321. https://doi.org/10.1136/bmjopen-2016-012321.
33. Jordi E, Pley C, Jowett M, Abou Jaoude GJ, Haghparast-Bidgoli H. Assessing the efficiency of countries in making progress towards universal health coverage: a data envelopment analysis of 172 countries. BMJ Global Health. 2020;5(10):e002992. https://doi.org/10.1136/bmjgh-2020-002992.
34. Cutler DM, Lleras-Muney A. Understanding differences in health behaviors by education. J Health Econ. 2010;29(1):1–28. https://doi.org/10.1016/j.jhealeco.2009.10.003.
35. Barasa E, Musiega A, Hanson K, et al. Level and determinants of county health system technical efficiency in Kenya: two stage data envelopment analysis. Cost Eff Resour Alloc. 2021;19(1):78. https://doi.org/10.1186/s12962-021-00332-1.
36. Sultan WIM, Crispim J. Measuring the efficiency of Palestinian public hospitals during 2010–2015: an application of a two-stage DEA method. BMC Health Serv Res. 2018;18(1):381. https://doi.org/10.1186/s12913-018-3228-1.
37. Audibert M, Mathonnat J, Pelissier A, Huang XX, Ma A. Health insurance reform and efficiency of township hospitals in rural China: an analysis from survey data. China Econ Rev. 2013;27:326–38. https://doi.org/10.1016/j.chieco.2013.01.004.
38. Binyaruka P, Anselmi L. Understanding efficiency and the effect of pay-for-performance across health facilities in Tanzania. BMJ Global Health. 2020;5(5):e002326. https://doi.org/10.1136/bmjgh-2020-002326.
39. Yang Y, Xue WJ, Liu J. Efficiency evaluation of county-level public hospitals in Hainan, China: a four-stage data envelope analysis model based on panel data. Chin Med J. 2021;134(7):876–8. https://doi.org/10.1097/CM9.0000000000001293.
40. Guillon M, Mathonnat J, Narantuya B, Dorjmyagmar B, Enkhtsetseg E. Exploring the efficiency of primary health care provision in rural and sparsely populated areas: a case study from Mongolia. Health Policy Plann. 2022;37(7):822–35. https://doi.org/10.1093/heapol/czac042.
41. Jing R, Xu T, Lai X, Mahmoudi E, Fang H. Technical Efficiency of Public and Private Hospitals in Beijing, China: a comparative study. IJERPH. 2019;17(1):82. https://doi.org/10.3390/ijerph17010082.
42. Ayiko R, Mujasi PN, Abaliwano J, et al. Levels, trends and determinants of technical efficiency of general hospitals in Uganda: data envelopment analysis and tobit regression analysis. BMC Health Serv Res. 2020;20(1):916. https://doi.org/10.1186/s12913-020-05746-w.
43. Kakemam E, Dargahi H. The Health Sector Evolution Plan and the Technical Efficiency of Public Hospitals in Iran. Iran J Public Health. 2019;48(9):1681–9.
44. Lee J, Lynch CA, Hashiguchi LO, et al. Interventions to improve district-level routine health data in low-income and middle-income countries: a systematic review. BMJ Global Health. 2021;6(6):e004223. https://doi.org/10.1136/bmjgh-2020-004223.
45. Lemma S, Janson A, Persson LÅ, Wickremasinghe D, Källestål C. Improving quality and use of routine health information system data in low- and middle-income countries: a scoping review. Francis JM. ed PLoS ONE. 2020;15(10):e0239683. https://doi.org/10.1371/journal.pone.0239683.
46. Gimbel S, Mwanza M, Nisingizwe MP, Michel C, Hirschhorn L, the AHI PHIT Partnership Collaborative. Improving data quality across 3 sub-saharan African countries using the Consolidated Framework for Implementation Research (CFIR): results from the African Health Initiative. BMC Health Serv Res. 2017;17(S3):828. https://doi.org/10.1186/s12913-017-2660-y.

Publisher's Note