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Technical Efficiency, Productivity, and Determinants of Technical Inefficiency of Local Hospitals in Oman: Using Data Envelopment Analysis

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Abstract: The purpose of this study is to evaluate the technical efficiency, productivity, and determinants of technical inefficiency in local hospitals in Oman, which are facing increasing resource constraints. Effective utilization of hospital resources is crucial for improving service delivery, ensuring equitable access, and maintaining the quality of healthcare. The study employs an input-oriented Data Envelopment Analysis (DEA) approach to assess the technical efficiency of 29 local hospitals under constant returns to scale (CRS), variable returns to scale (VRS), and scale efficiency (SE) using data from 2018. Additionally, a Tobit regression model is used to identify the determinants of hospital inefficiency, and the DEA-based Malmquist Productivity Index (MPI) is applied to panel data from 2015 to 2018 to measure Total Factor Productivity Change (TFPCH). The findings reveal that 75.8% of the local hospitals were technically efficient under VRS and SE assumptions, while 79.3% achieved technical efficiency under the CRS assumption. The average technical efficiency scores under CRS, VRS, and SE were 96%, 97%, and 99%, respectively. The Tobit model indicates that the number of physicians and pharmacists negatively impacts the VRS efficiency score, while the number of outpatient visits has a positive effect. Productivity growth of 18.1% was observed over the study period, mainly driven by a 42.6% increase in technological change. The study concludes that while most local hospitals in Oman are technically efficient, there is still room for improvement. The findings imply that targeted interventions, such as optimizing the allocation of human resources and leveraging technological advancements, could enhance the overall efficiency and productivity of the healthcare system in Oman.

Keywords: Oman Local Hospital, Technical Efficiency, Productivity, Data Envelopment Analysis, Tobit Model, Malmquist Productivity Indices, Oman.

1. Introduction

Ministry The Ministry of Health is the leading healthcare provider in Oman for both primary and specialized healthcare. Specialized healthcare is provided through four levels of hospitals: national hospitals, governorate hospitals, Wilayat hospitals, and local hospitals (Mwihia, M'Imunya, Mwabu, Kioko, & Estambale, 2018). National hospitals provide tertiary healthcare services at the national level, and all these hospitals are in Muscat (the capital). Governorate hospitals are in the centre of each governorate and provide secondary and tertiary healthcare to people in the governorate. Wilayat Hospitals offer primary and secondary healthcare to people in the same or nearby Wilayat. Local hospitals are the smallest hospitals in terms of size and level of health service provided. Local hospitals offer primary healthcare and some inpatient health services to people in nearby villages. Currently, there are 30 local hospitals in Oman with an average bed size of 20.5 (MOH, 2019).

Oman's health system increasingly faces critical resource constraints in delivering the same or better health services. Many factors contribute to such pressure on scarce resources, including the high prevalence of chronic diseases, a growing and ageing population, higher community expectations, a shortage of human resources, and more expensive medical technologies. Additionally, the poor macroeconomic performance, which depends heavily on oil, may lead to cutbacks in governmental spending on health. Oil and gas are the primary sources of government revenue in Oman, and the financing of Oman's health system depends mainly on governmental support by almost 81% (MOH, 2014). During economic crises, the health sector is often one of the most affected areas due to government budget cutbacks. For example, the total expenditure of the Ministry of Health dropped significantly from 892.2 million R.O. in 2015 to 699.5 million R.O. in 2018 (NCSI, 2020). Hospitals and specialized healthcare are the most integral and costly aspects of the healthcare system. In some developed countries like Australia, hospitals consume an average of 40% of the total health expenditure (Canberra, 2006; Kamil, Kruger, & Tennant, 2021).

In developing countries, the percentage is much higher, where 50% to 80% of health expenditure is spent on specialized healthcare services (Newbrander, Barnum,

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Kutzin, & Organization, 1992). In Oman, hospitals operated by the Ministry of Health consumed approximately 54% of the total recurrent expenditure, where salaries of medical and paramedical staff represent approximately 78.6% of the cost of hospitals (MOH, 2014). There is evidence to suggest that inefficiency is a significant problem in all health systems, especially in developing countries (Zere, 2000). World Health Organization (WHO) statistics suggest that nearly 20% to 40% of the total global health expenditures are wasted due to inefficiency (WHO, 2010). Inefficient use of health system resources causes serious problems that may harm social cohesion, the health system production process, and overall social surplus. Therefore, better utilization of hospital resources will increase the opportunity to serve additional patients and enable the redistribution of potential resources to ensure improvement in health outcomes, equity, accessibility, and the delivery of sustainable quality care.

The purpose of this study is to evaluate the technical efficiency, productivity, and determinants of technical inefficiency of 29 local hospitals affiliated with the Ministry of Health in Oman. To guide this investigation, the study seeks to answer the key research question: What are the key factors influencing the technical efficiency of local hospitals in Oman, and how can these hospitals improve their resource utilization to better serve the population? Ramanathan (2005) examined the technical efficiency and productivity of 20 regional hospitals (secondary and tertiary level hospitals) in Oman using Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI). However, no previous study has estimated the technical efficiency of local hospitals in Oman. It is hoped that findings can fill the knowledge gap regarding hospital facilities' performance in Oman and inform policy formulation around efficient resource allocation decisions. Better utilization of hospital resources will enable more services to be provided and allow the redistribution of potential resources to ensure equity, accessibility, and the delivery of sustainable quality care.

2. Literature Review

In 1951, Koopmans defined the technical efficiency of a decision-making unit (DMU) theoretically, proposing that it is impossible to improve any inputs or outputs of the production process without worsening other inputs or outputs (Ruggiero, 1996). Building upon this, Farrell (1957) introduced the concept of measuring the technical efficiency of a particular DMU in relation to the efficiency score of similar DMUs within the same industry. Efficient DMUs operate at the production possibility frontier, with a technical efficiency score equal to one, whereas inefficient DMUs operate below the production possibility frontier, with scores less than one (WHO, 2010).

Technical efficiency in healthcare can be evaluated using two primary approaches: input-oriented and output-oriented. The input-oriented approach, more commonly applied to public institutions like hospitals, focuses on minimizing inputs while maintaining the same level of output. This approach is particularly relevant for public hospitals where management has limited flexibility to alter output levels but can potentially reduce resource inputs. Alatawi, Niessen, and Khan (2020) applied an input-oriented approach to assess the technical efficiency of public hospitals in Saudi Arabia, revealing that 75.8% of these hospitals were inefficient.

On the other hand, the output-oriented approach, although less commonly used in public institutions, seeks to maximize outputs with a fixed level of inputs. For instance, Küçük, Özsoy, and Balkan (2020) employed the output-oriented method to measure the technical efficiency of public hospitals in Turkey. Each approach offers unique insights, but the choice between them often depends on the specific context and goals of the efficiency evaluation.

Data Envelopment Analysis (DEA) is the most prevalent method for measuring technical efficiency in healthcare settings, followed by Stochastic Frontier Analysis (SFA) (Cylus, Papanicolas, Smith, & Organization, 2016). DEA is a non-parametric method introduced by Charnes, Cooper, and Rhodes in 1978, which estimates the efficiency of DMUs relative to comparable units. DEA's ability to incorporate multiple inputs and outputs without requiring pre-specification assumptions makes it particularly useful in complex healthcare environments (Alatawi et al., 2020).

The main drawbacks of DEA include its inability to account for random errors and its failure to facilitate statistical analysis of inefficiency hypotheses (Sena, 1999). Moreover, DEA does not support across-study or cross-country comparisons, which limits its generalizability (wealth, 1997). Despite these limitations, DEA remains a favored tool in healthcare efficiency studies due to its flexibility and applicability to small sample sizes (Faruk & Rahaman, 2015).

Several DEA models have been developed to estimate technical efficiency, with the most commonly used being the Charnes, Cooper, and Rhodes (CCR) model and the Banker, Charne, Cooper (BCC) model. The CCR model, grounded in the constant return to scale assumption, is appropriate for hospitals operating at an optimal level (Zere, 2000). However, since most hospitals operate below this level, the CCR model may not always be the best fit for healthcare efficiency studies.

To address this, the BCC model was introduced in 1984, adopting a variable returns to scale (VRS) assumption. The BCC model's ability to distinguish between pure technical efficiency and scale efficiency makes it more suitable for assessing hospitals that do not operate at optimal scale (Kirigia et al., 2010). By applying the BCC model, researchers can gain a more nuanced understanding of the factors contributing to inefficiency in healthcare settings.

Recent advancements in DEA applications have seen its integration with other analytical methods to enhance robustness. For example, combining DEA with regression analysis allows for a deeper examination of the determinants of inefficiency and the exploration of relationships between efficiency scores and external factors. This integrated approach has been particularly valuable in healthcare, where multiple variables and complex interactions often influence efficiency outcomes.

DEA's application in healthcare has significantly impacted policy formulation, particularly in resource allocation and performance benchmarking. By identifying inefficiencies and areas for improvement, DEA findings have informed policy decisions aimed at optimizing resource use and improving healthcare delivery. Studies from both developed and developing countries demonstrate DEA's utility in shaping health policy and driving reforms that enhance system efficiency.

While DEA offers substantial benefits in evaluating healthcare efficiency, it also presents challenges. These include issues related to data quality, the selection of appropriate inputs and outputs, and the interpretation of results. Additionally, the absence of a standardized approach for applying DEA across different healthcare systems complicates cross-country comparisons and limits the generalizability of findings.

Although DEA is widely used within countries, its application in cross-country comparisons remains limited due to methodological challenges. Differences in healthcare systems, cultural contexts, and economic environments complicate the direct comparison of efficiency scores across countries. However, when carefully designed, cross-country DEA studies can offer valuable insights into the relative efficiency of healthcare systems and highlight best practices that could be adopted in different settings.

The application of DEA in healthcare continues to evolve, with recent trends focusing on areas such as the efficiency of telemedicine services and the impact of the COVID-19 pandemic on hospital operations. Future research could explore the role of DEA in evaluating the efficiency of healthcare delivery in rural versus urban settings, or in monitoring the long-term effects of healthcare reforms. Additionally, there is a growing interest in integrating DEA with machine learning techniques to predict efficiency trends and optimize healthcare resource allocation further.).

3. Research Methodology

Input An input-oriented Data Envelopment Analysis (DEA) and a Tobit model were employed to assess the relative efficiency and determinants of technical inefficiency of local hospitals in Oman using 2018 data. Additionally, the DEA-based Malmquist Productivity Index was used to assess changes in the productivity of local hospitals over the period from 2015 to 2018. Input and output data were obtained from the Ministry of Health’s Annual Health Reports from 2015-2018. The study sample comprised 29 local hospitals affiliated with the Ministry of Health in Oman. Secondary and tertiary hospitals, such as National Hospitals, Governorate Hospitals, and Wilayat Hospitals, were excluded from the study due to their different characteristics and advanced levels of healthcare. Al-Rahma Hospital, a primary healthcare hospital for infectious diseases, was also excluded because it offers a limited range of services compared to other local hospitals. In addition, primary healthcare centers, other governmental hospitals, and private hospitals were excluded from the study.

This study included seven input variables and three output variables. The input variables were bed size (a proxy for capital), number of physicians, number of nurses, number of pharmacists, number of other personnel, number of X-rays, and total number of laboratory investigations. These variables were chosen because human resources consumed approximately 78.6% of hospital expenditure within the Ministry of Health in Oman (MOH, 2014). The number of X-rays and laboratory investigations were selected as input variables under the category of operational expenses, as they represent significant components of hospital expenditure. Pharmaceutical costs were not included due to the unavailability of data. Since these hospitals primarily provide basic healthcare, they only have X-ray units, with more advanced radiological techniques like CT scans and MRI unavailable. The output variables included the number of inpatient days, number of outpatient visits, and number of deliveries (both vaginal and cesarean). These variables capture the majority of the activities performed in these hospitals.

In the second stage of data analysis, the Tobit model was used to assess the determinants of hospital inefficiency using the 2018 data set. The Tobit model, a non-linear statistical model proposed by James Tobin in 1958, examines the relationship between a dependent variable (Y) and independent variables (Xi). Simar and Wilson (2000) argue that the Tobit model provides consistent estimation in the second stage, given that the efficiency scores are right-censored. The Variable Returns to Scale (VRS) scores from 2018 were used as the dependent variable. The independent variables included hospital bed size, population density in the governorate, number of nurses, number of pharmacists, number of other personnel, number of inpatient days, bed occupancy rate, average inpatient length of stay, physician-to-bed ratio, and nurse-to-bed ratio. These independent variables were chosen because factors such as hospital location, size, and the improper distribution of human resources are primary drivers of technical inefficiency in hospitals.

In the third stage of data analysis, the DEA-based Malmquist Productivity Index (MPI) was applied to the panel data to measure Total Factor Productivity Change (TFPCH), Technological Change (TECCH), and Technical Efficiency Change (TECH). A Malmquist productivity score above one indicates productivity growth, while a score of less than one indicates productivity decline or regression. Following Färe et al. (1994), the

Malmquist Productivity Index has become a standard method for evaluating productivity using a non-parametric model (Zere, 2000).

4. Results And Analysis

The descriptive statistics of inputs and outputs variables showed a wide variation in bed size among the selected hospitals, with an average bed size of 20.5 beds. The smallest hospitals have a bed size of 6 beds, whereas the largest hospital has a bed size of 41 beds. Among the workforce, the number of other personnel followed by the number of nurses represents the highest proportion of the workforce. The average number of physicians among the sample size is 11.1 physicians per hospital. X-ray and delivery units are not available in some hospitals. Summary statistics of inputs and output variables of the 29 local hospitals are presented in Table 1.

Table 1: Descriptive Statistics Of Input And Output Variables

Variables	observation	Mean	SD	Minimum	Maximum
No. of Beds	29	20.5	9.3	6	41
No. of Physicians	29	11.1	9.8	1	33
No. of Nurses	29	30.8	21.5	7	88
No. of pharmacists	29	6.2	4.6	1	18
No. of other Personal	29	48.1	26.6	16	109
No. of X-rays	29	2970.1	3164.7	0	13001
No. of Laboratory Investigations	29	52988.3	73022.2	1780	273240
No. of Inpatients Days	29	2077.7	2017.1	37	7665
No. of Outpatient visits	29	52116.3	37055.3	6286	141832
No. of Deliveries	29	82.9	125.1	0	503

Source: Calculated by author.

Table 2 shows the efficiency scores of locals in 2018 under constant return to scale (CRS), variable return to scale (VRS) and scale efficiency (SE). The findings of the first stage DEA analysis suggested that 22 (75.8%) hospitals were technically efficient under VRS and SE assumptions, and 23 (79.3%) hospitals achieved technical efficiency under CRS. Among the seven scale inefficient hospitals, four of them operate at increasing return to scale (IRS), and three operate at decreasing return to scale (DRS). The average technical efficiency score under CRS, VRS and SE were 96%, 97% and 99%, respectively. In addition, the results presented in Table 3 indicated that the relatively larger hospitals (26-40 beds) were less technically efficient than smaller hospitals under both CRS and VRS assumptions.

Table 2: Technical Efficiency Score Under Constant Return To Scale, Variable Return To Scale And Scale Efficiency

DMU	Hospital	Beds	CRS	VRS	SE	RTS
1	Quryyat Hospital	29	0.64	0.67	0.97	IRS
2	Madinat Al-Haqq Hospital	12	1	1	1	-
3	Taqah Hospital	23	1	1	1	-
4	Twi Atyr Hospital	12	0.96	0.97	0.96	DRS
5	Mirbat Hospital	28	1	1	1	-
6	Rakhyut Hospital	18	1	1	1	-
7	Sadah Hospital	18	0.93	0.95	0.98	IRS
8	Daba Hospital	40	0.65	0.67	0.98	DRS
9	Bukha Hospital	16	0.84	0.86	0.97	IRS
10	Wadi Al-Jizzi Hospital	6	1	1	1	-
11	Al-Jabal Al-Akhdar Hospital	24	1	1	1	-
12	Adam Hospital	30	1	1	1	-
13	Izki Hospital	25	1	1	1	-
14	Wadi Hibi Hospital	18	1	1	1	-
15	Wadi Al-Sarami Hospital	9	1	1	1	-
16	Wadi Al-Hawasinah Hospital	10	0.89	1	0.89	IRS
17	Wadi Bani Ghafir Hospital	15	1	1	1	-
18	Wadi Al-Haymli Hospital	17	1	1	1	-
19	Wadi Bani Kharus Hospital	13	1	1	1	-
20	Wadi Mistal Hospital	16	1	1	1	-
21	Jaalan Bani Bu Hasan Hospital	41	1	1	1	-
22	Masirah Hospital	40	0.98	0.98	1	DRS
23	Samad Al-shan Hospital	24	1	1	1	-
24	Bidiyah Hospital	24	1	1	1	-
25	Wadi Bani Khalid Hospital	13	1	1	1	-
26	Wadi Dama Wa Al-Taiyn Hospital	26	1	1	1	-

27	Yanqul Hospital	12	1	1	1	-
28	Al-Duqum Hospital	16	1	1	1	-
29	Al-Jazir Hospital	20	1	1	1	-
	Mean	20.5	0.96	0.97	0.99	-

Source: Calculated by author.

Table 3: Average Technical Efficiency Score Per Size of The Hospitals.

Beds size	Constant return to scale (CRS)	Variable return to scale (VRS)	Scale Efficiency (SE)
6 - 15	0.98	0.99	0.98
16 - 25	0.98	0.98	0.99
26 - 40	0.89	0.90	0.99

Source: Calculated by author.

The results of the Tobit model (Table 4) show that most explanatory variables were negatively correlated with the VRS score except bed occupancy rate and nurses-to-bed ratio. Hospital bed size (P<0.01, 95% CI: -0.006, -0.001), the population density of the governorate (P<0.01, 95% CI: -0.0008, -0.0003), and the physician-to-bed ratio (P<0.01, 95% CI: -0.28, -0.05) were significantly correlated with VRS. However, the coefficient is very small (almost zero) for all variables.

Table 4l: Tobit Regression Results Of Determinants Of Technical Inefficiency

vrsscore	Coef.	Std.Err.	t	p>|t|	[95% Conf. Interval]
Hospital bed size	-0.0035077	0.0011696	- 3.00	0.006	[-0.0059271] - [-0.0010883]
Governorate population density	-0.0005466	0.0001335	- 4.10	0.000	[-0.0008227] - [-0.0002705]
Average inpatients cases	-0.0066	0.0123587	- 0.53	0.598	[-0.032166] - [0.018966]
Bed occupancy rate	0.0011026	0.0006105	1.81	0.084	[-0.0001604] - [0.0023656]
Physician bed ratio	-0.1677493	0.0565668	- 2.97	0.007	[-0.2847667] - [-0.0507319]
Nurse bed ratio	0.0568206	0.0285893	1.99	0.059	[-0.0023208] - [0.115962]
_cons	1.052478	0.0400564	26.27	0.000	[0.9696149] - [1.135341]
Var (e.vrs score)	0.0028257	0.0007421			[0.0016413] - [0.0048647]

Source: Calculated by author.

Malmquist productivity indices were used to estimate the Total Factor Productivity change (TFPCH), technical efficiency change (TECH) and technological change (TECCH) over three consecutive pairs of years (2015/2016, 2016/2017,2017/2018), as shown in Figure 1. The finding suggested that there was a productivity growth of 18.1% over the selected study period. The total factor productivity growth was mainly attributed to technological change, which improved by 42.6%. On the other hand, there was a significant drop in technical efficiency by 28.7% during the same period. The technical efficiency change showed a declining trend in the 2016/2017 period by 0.97.

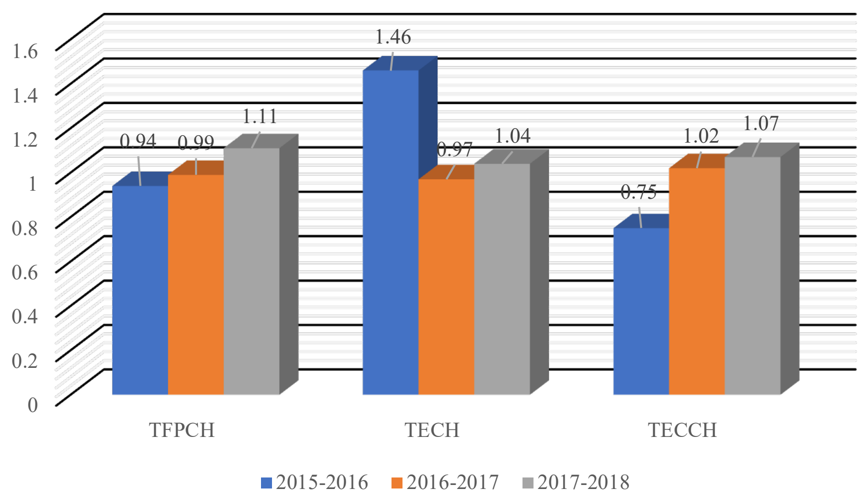

Figure 1: Malmquist Indices For Local Hospitals in Oman (2015-2018).

5. Discussion

The technical efficiency of local hospitals in Oman in 2018 was measured using the input-oriented DEA model under VRS, CRS, and SE assumptions. The findings suggest that 75.8% of local hospitals were technically efficient under VRS and SE assumptions, while 79.3% achieved technical efficiency under CRS. These findings are consistent with other studies that assess the technical efficiency of small-sized hospitals. For example, Alatawi et al. (2020) used an input-oriented approach to assess the technical efficiency of public hospitals in Saudi Arabia, where they evaluated 91 public hospitals affiliated with the Ministry of Health. The results indicated that 75.8% of public hospitals in Saudi Arabia were inefficient. Similarly, Ahmed et al. (2019) examined the technical efficiency of 65 district hospitals in Bangladesh using a DEA input-oriented approach and found that the average SE, VRS, and CRS scores were 85%, 92%, and 79%, respectively.

Our results suggest that smaller hospitals achieved higher technical efficiency scores than larger hospitals. These results are consistent with studies that used the DEA approach to analyze Kenyan public hospitals, revealing that small hospitals are more efficient than large hospitals, with efficiency levels ranging from 74-91% in small DMUs and from 57-78% in large DMUs (Alatawi et al., 2020). The higher efficiency scores among smaller hospitals might be attributed to their location in rural areas where there is a shortage of other health facilities. Additionally, local hospitals lack teaching and research capacity and most commonly receive non-critical cases, which may contribute to their higher efficiency.

Determination of input and output slacks might help hospital managers improve technical efficiency at the individual hospital level. For instance, the input and output slacks of inefficient hospitals are presented in Table 5. For example, the technical efficiency score of DMU1 might be improved by reducing the input slacks: other personnel by 32, physicians by 10.5, nurses by 18.1, pharmacists by 0.15, and X-ray by 1193.2. Similarly, the technical efficiency score of DMU4 might be improved by reducing input slacks: other personnel by 20.6, nurses by 6.1, and X-ray by 196.7, while increasing output slacks: number of inpatient days by 196.7 and the number of deliveries by 8.1.

Table 5: Input And Output Slacks Of Inefficient Hospitals

DMU	Input Slacks Beds	Other personal	Physicians	nurses	pharmacists	x-ray	investigation	Output Slacks inpatient	outpatients	deliveries
1	-	32.0	10.5	18.1	0.15	1193.2	-	-	-	-
4	-	20.6	-	6.1	-	196.7	-	196.7	-	8.1
7	10.1	24.7	-	5.5	-	265.2	1122.9	-	-	24.5
8	6.8	18.9	11.8	-	-	-	0.003	6.2	-	-
9	-	10.9	1.5	2.1	0.82	-	-	-	-	10.6
16	-	3.8	-	1.4	0.015	-	-	-	-	-
22	13.0	-	20.5	48	3.1	643.7	-	-	-	-

Source: Calculated by author.

The regression analysis findings suggest that only three variables were significantly correlated with the VRS score: hospital size, population density, and physician-to-bed ratio. The results indicate that if the hospital size increases by one unit, the VRS efficiency score decreases by 0.004, given other variables remain constant. Similarly, if population density and physician-to-bed ratio increase by one unit, the VRS efficiency score decreases by 0.1 and 0.0005, respectively. However, the coefficients in all three cases are very small (almost zero), indicating that these results are unlikely to make any tangible difference.

The Malmquist Productivity Indices of local hospitals over the three consecutive pairs of years (2015/2016, 2016/2017, 2017/2018) indicate a total factor productivity growth of 18.1%, primarily attributed to technological change, which improved by 42.6%. Over the same period, there was a significant drop in technical efficiency change by 28.7%. The technological growth could be partially explained by the improvement in staff skills, the health information system, and the referral system rather than improvements in medical equipment. Additionally, the technological growth might be attributed to the more efficient use of scarce resources resulting from significant cutbacks in the Ministry of Health budgets due to the economic crisis.

Several limitations have been recognized in this study. Firstly, the study does not consider the severity of admitted cases and the quality of hospital services, assuming that quality is constant across all hospitals. This assumption may not hold, as the level and quality of healthcare services are not uniform, potentially introducing bias to the results. Secondly, there is a non-availability of data related to the research and teaching function outputs, which is likely to underestimate the level of efficiency, particularly for hospitals with teaching functions. However, these limitations did not significantly affect the estimated technical efficiency scores because teaching and research functions constitute a very small proportion of overall output.

This study is the first to assess the technical efficiency, productivity, and determinants of technical inefficiency of local hospitals in Oman. Further studies are required to evaluate the technical efficiency and productivity of other public and private healthcare institutions in Oman. These studies should be conducted routinely every two or three years. Furthermore, it is crucial to include a quality variable in future studies when examining the technical efficiency and productivity of healthcare services.

6. Conclusion

This study evaluates the technical efficiency, productivity, and determinants of technical inefficiency of local hospitals in Oman affiliated with the Ministry of Health using 2018 data. The findings suggest that 75.8% of local hospitals were technically efficient under VRS and SE assumptions, and 79.3% achieved technical efficiency under CRS. The average technical efficiency scores under CRS, VRS, and SE were 96%, 97%, and 99%, respectively. The results of the Tobit regression analysis indicate that hospital size, population density, and physician-to-bed ratio are significantly correlated with the VRS score. Additionally, the productivity of local hospitals increased by 15.8% during the period 2015-2018, primarily due to a significant technological change of 42.6%. These findings highlight opportunities for improving the performance of local hospitals. Further studies are needed to measure the technical efficiency and productivity of other components of the health system in Oman to generalize the findings at the national level.

7. Limitations And Future Research

This study has several limitations that should be considered when interpreting the findings. First, the analysis did not account for the severity of cases admitted to the hospitals or the quality of services provided. The assumption that quality is consistent across all hospitals may not hold, as variations in service levels and quality likely exist, potentially introducing bias into the results. Additionally, the study did not include data related to research and teaching functions, which are important aspects of hospital operations. The exclusion of these outputs may lead to an underestimation of technical efficiency, particularly for hospitals with significant teaching functions. However, given that research and teaching constitute a relatively small portion of the overall output for most hospitals, this limitation is unlikely to have significantly impacted the overall findings.

Looking ahead, further research is necessary to build on these findings. Future studies should incorporate quality measures into the evaluation of technical efficiency and productivity to provide a more comprehensive assessment of hospital performance. Moreover, it would be beneficial to extend this research to include other components of the health system in Oman, such as primary healthcare centers and private hospitals, to provide a more complete picture of healthcare efficiency at the national level. Conducting these studies on a routine basis, every two to three years would enable policymakers to monitor progress and make informed decisions to enhance the efficiency and effectiveness of the healthcare system in Oman.

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