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ORIGINAL ARTICLE

Analysis of the efficiency of medical device utilisation in OECD countries

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ABSTRACT

Objective: The aim of this descriptive and cross-sectional study is to assess the efficiency of medical device utilisation in OECD countries in the context of health outcomes using Data Envelopment Analysis (DEA).

Method: The sample of the study consists of 28 OECD countries. The medical device utilisation efficiency of the countries was evaluated within the framework of the input variables computed tomography scanners (CT), magnetic resonance imaging units (MRI), positron emission tomography scanners (PET), gamma cameras (GAM), mammography machines (MAM), radiotherapy equipment (RT) per million inhabitants and the output variables life expectancy (LE), satisfaction with healthcare system (SH) and perceived health status (PH). The data for 2022 were obtained from the OECD database. As this study used publicly available, aggregate data, no ethics committee approval was required. DEA was performed with input-oriented constant returns to scale (CCR) and variable returns to scale (BCC) models.

Results: According to all models, Canada, Czechia, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland and Türkiye are efficient while Finland, Greece, Italy and Slovak Republic are inefficient. The country with the lowest efficiency is the United States according to CCR model and Greece according to BCC model. Türkiye, Israel and Poland were found to be the most referenced countries. MRI, CT and MAM are the input variables most in need of improvement.

Conclusion: It was found that 46% of the OECD countries evaluated in the study according to BCC model and 86% according to CCR model are relatively efficient in terms of medical device utilisation. It is recommended that inefficient countries should improve their idle inputs and avoid unnecessary use.

Keywords: Data Envelopment Analysis, Efficiency, Health, Medical Device, OECD

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INTRODUCTION

The health sector is both labour-intensive and technologically dependent. Technological advances in the medical device sector have had a positive impact on health services. The extensive use of medical devices in the diagnosis of diseases and the evaluation of treatment outcomes is a key factor in this development. The utilisation of medical devices in the decision-making process for health services has been shown to prevent medical errors. However, as in every field, the benefits from the use of medical devices have a marginal point. However, if this threshold is exceeded, the increasing use of medical devices may lead to adverse consequences, including the failure to deliver intended benefits.Excessive utilisation can result in a deterioration in health outcomes and an escalation in unnecessary health expenditures. In the context of constrained health sector resources and escalating health expenditures, it becomes imperative to make judicious decisions regarding medical device investment. A pivotal initial step in this direction is to assess the efficiency of existing medical devices. This process will yield evidence-based information on underutilised medical devices and areas where improvement is required, thereby informing optimal investment decisions in medical devices.

The development of the medical device industry has attracted much attention in the context of the increasing demand for healthcare services[1]. The global medical device market was valued at USD 455.50 billion in 2022 and is projected to reach USD 756.59 billion by 2031, representing an increase from USD 481.92 billion in 2023[2]. United States (US), Japan, Germany and China are responsible for the world's largest medical device markets[1,3]. In high income country, the medical device market is characterised by well-developed regulatory systems, high investment in research and development, and innovation intensity, while low and middle income countries often face challenges related to inadequate regulatory frameworks and limited access to advanced medical technologies. The medical device industry in low and middle income countries is often dependent on imported devices, which can be costly and limit local innovation[4,5]. It is imperative for the effectiveness of health systems in all countries, both importers and exporters of medical devices, to assess the effective utilisation of medical devices. The effectiveness of medical devices can be measured in terms of technical capacity, diagnostic accuracy, diagnostic and therapeutic impact, and various health outcomes[6]. Measuring the effectiveness of medical device use, in particular, contributes to the efficient use of healthcare system resources, the prevention of unnecessary spending, and the improvement of health outcomes.

Different analysis techniques are used to evaluate the efficiency of various areas in the health sector. These methods encompass both quantitative and multi-criteria analysis approaches, which reflect the complex and multidimensional structure of healthcare systems. Data Envelopment Analysis (DEA), one of the most important techniques used in this field, is widely recognised for its ability to evaluate efficiency by comparing multiple inputs and outputs. This non-parametric method facilitates an objective evaluation of relative efficiency among comparison units, with the assessment being based on the maximum output that can be obtained from specific inputs[7,8]. A substantial body of research has demonstrated the extensive utilisation of DEA over numerous years in the evaluation of healthcare service efficiency within diverse contexts. In these studies, health services, health institutions, or geographical units are evaluated based on various health indicators[9,10]. While there are studies that use medical device indicators as variables in effectiveness evaluations[11], no study has been found that focuses on evaluating the effectiveness of countries' medical devices using DEA. Given the widespread use of DEA in the healthcare sector, its non-use in measuring the effectiveness of medical devices in countries points to a gap in the literature. Conversely, studies evaluating the effectiveness of healthcare systems and medical devices directly using medical device indicators are pretty limited[12-18]. As per the findings of Ilgün et al.[16], the efficiency of medical imaging devices in Turkish provinces was evaluated through the utilisation of the DEA methodology. Another study utilized medical device indicators as variables to measure the effectiveness of healthcare systems using Multi Criteria Decision Making (MCDM) techniques[15]. Subsequently, De Domenico et al.[12] conducted a comprehensive evaluation of the medical device performance of health institutions in Italy, utilising the Panel Data Analysis approach. Abiş and Çapar[17] evaluated medical device investments at the OECD level using panel data analysis. Yüksel[18] evaluated the efficiency of medical imaging devices in Turkish hospitals using DEA. Wei et al.[19] conducted a study to investigate the relationship between hospital efficiency and the use of medical devices. In some studies, medical device performance has been compared numerically[13,14]. In this study, however, the medical device utilisation efficiency of OECD countries is evaluated with DEA within the framework of health outcomes, a departure from the literature. The present study aims to evaluate the efficiency of medical device utilisation in OECD countries in the context of health outcomes using the DEA method. While previous research has assessed efficiency at national or institutional levels, this study contributes by applying DEA to cross-national device-level indicators within the OECD. The absence of extensive research in this domain, coupled with the pivotal role of medical device efficiency, underscores the originality and significance of this study within the existing literature.

METHODS

The objective of the present study is to evaluate the utilisation efficiency of medical devices in OECD countries within the framework of health outcomes by using the DEA methodology. The research was designed as a descriptive and cross-sectional study. It was conducted using secondary data for 28 OECD countries obtained from open-access datasets.

Selection of Decision Making Units

In data envelopment analysis, the units whose relative efficiency is evaluated are termed decision-making units (DMUs). For the results to be meaningful, the selected DMU must be distributed evenly across the study population. The DMUs of this research are OECD countries, which constitute an ideal group for making a meaningful and consistent comparison in economic, social and environmental terms. Indeed, this international organisation, which works to 'create better policies for better lives', consists of low, middle and high income countries. The OECD comprises 38 member countries, spanning the continents of North America, South America, Europe, and Asia-Pacific. The extensive data network of OECD countries, which facilitates the establishment of evidence-based international standards, underscores their aptitude for conducting meaningful and consistent comparisons[20]. However, it should be noted that data pertaining to all the variables that are to be utilised in the evaluation of medical device effectiveness were not available for 10 of the 38 member countries. Consequently, the study incorporated data from 28 OECD member countries that possessed complete data sets. The countries in which medical device effectiveness was evaluated are as follows: Australia, Austria, Belgium, Canada, Czechia, Denmark, Estonia, Finland, Greece, Hungary, Iceland, Ireland, Israel, Italy, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, Türkiye and US.

In the process of selecting DMUs, two primary perspectives emerge regarding the relationship between variables. Firstly, it is imperative to ensure that the number of decision-making units is at least twice the number of variables. Secondly, given the DMU N, the input variable k, and the output variable t, the condition N≥maximum [k x t, 3(k + t)] must be satisfied[21] The present study encompasses 28 DMUs and nine variables, comprising six inputs and three outputs. It can be demonstrated that the first condition is satisfied by the calculation 28> (9x2 = 28>18. It can be demonstrated that the second condition is satisfied by virtue of the fact that 28 is greater than 27, as evidenced by the following calculation: 28≥ maximum [6x3, 3(6+3)]. In this regard, it is evident that the DMU selection was conducted in accordance with the regulations stipulated by the DEA.

Data Set and Variables

In the study, nine variables were employed for the medical device capacities of the countries. The data for the variables were obtained from the OECD's open access database. No individual-level data were used, and no intervention was applied; therefore, formal ethical approval was not necessary. As input variables, the number of medical devices per 1,000,000 inhabitants for which data are available were included. Accordingly, the input variables are computed tomography scanners per million inhabitants (CT), magnetic resonance imaging units per million inhabitants (MRI), positron emission tomography scanners per million inhabitants (PET), gamma cameras per million inhabitants (GAM), mammography machines per million inhabitants (MAM), radiotherapy equipment per million inhabitants (RT). The output variables are life expectancy (LE), satisfaction with healthcare system (SH) and perceived health status (PH) in the context of health outcomes that are directly or indirectly influenced by the utilisation of medical devices. Indeed, the employment of medical devices has been demonstrated to exert a favourable impact on public health, satisfaction, and health perception of individuals by facilitating more precise diagnosis and efficacious treatment opportunities. Research has also identified a correlation between such health outcomes and the capacities of medical devices[13,14].

Among the input variables, LE presents statistics on life expectancy at birth. SH shows the percentage of satisfaction with health service provision. PH refers to the percentage of the population aged[15] and over who report their health as "good/very good" (or excellent). Accordingly, LE, SH and PH indicators are output variables that show how medical devices contribute to health outcomes. Data for input and output variables for 2022 were obtained from OECD and Eurostat databases[22,23]. Since the most up-to-date data available belong to this year, 2022 was determined as the research period.

The selection of input and output variables to be used in DEA may vary depending on the research topic. However, the suitability and representativeness of the variables used to measure effectiveness in healthcare systems are of decisive importance. In this regard, the purpose of the research and similar studies previously conducted in the literature informed the selection of variables. As the primary objective of the research is to measure the effectiveness of medical devices in the context of health outcomes, the number of medical devices was used as the input variable. The output variables selected for analysis were LE, SH, and PH, which are frequently employed in DEA studies to represent health outcomes. However, the number of variables was determined by considering the mathematical relationship that should exist between the input and output variables. A comprehensive overview of this subject can be found in the dedicated section on the selection of decision-making units. Furthermore, the quality of the analysis is contingent on the number of variables utilised. The presence of an excessive number of input and output variables within the model has been shown to compromise the efficacy of differentiation between units. This factor could lead to measurement errors. It is therefore recommended that correlation analysis be employed to examine the relationships between input and output variables prior to establishing the model. Consequently, variables demonstrating a high degree of correlation are excluded, thereby preventing the model from becoming excessively complex with superfluous variables[24]. The relationship between variables was evaluated using Spearman correlation analysis, as the data were not normally distributed. It was determined that the correlation coefficients calculated in the SPSS 24.0 programme varied between -0.18 and 0.66 and that there was no high correlation between the variables. Thus, the suitability of the variables for analysis was tested (Table 1).

Data Analysis

The minimum, maximum, mean, median and standard deviation values are presented as descriptive statistics for the variables utilised in the study. The medical device utilisation efficiency of the DMUs within the framework of health outcomes was evaluated by DEA. The STATA 18 programme was employed in the analysis of the data. To analyze data in DEA, it is first necessary to determine the research model. In DEA, the model can be designed to be input- or output-oriented, depending on the research purpose and the level of control over inputs and outputs. Following the determination of orientation, scale-dependent returns are taken into consideration. Scale-dependent returns are indicative of the effect of changes in inputs on outputs; that is, they demonstrate whether an increase in inputs has a proportional, lesser, or greater effect on outputs. In instances where an increase in inputs is anticipated to result in a proportional change in outputs, the CCR model is employed. Conversely, if a proportional change is not expected, the BCC model is utilised[25]. This research was conducted based on input-oriented CCR and BCC models. Input-oriented DEA focuses on minimising the inputs used to achieve a certain level of output. This model is particularly in inputs has a proportional, lesser, or greater effect on outputs. In instances where an increase in inputs is anticipated to result in a proportional change in outputs, the CCR model is employed. Conversely, if a proportional change is not expected, the BCC model is utilised[25]. This research was conducted based on input-oriented CCR and BCC models. Input-oriented DEA focuses on minimising the inputs used to achieve a certain level of output. This model is particularly useful in contexts where resources are limited and the aim is to optimise resource use without compromising service delivery. In healthcare systems, direct control over outputs is limited, but managing inputs is more feasible[26,27]. In this context, an input-oriented model is considered more appropriate for evaluating the effective use of resources. Given the capacity to exercise control over the input of medical devices, the model for the study was deemed input-oriented. The mathematical representation of input-oriented models is provided below.

Table 1. Correlation coefficients of variables

	CT	MRI	PET	GAM	MAM	RT	LE	SH	PH
CT	1.00	0.58**	0.32	0.03	0.58**	0.43*	0.17	0.04	0.16
MRI		1.00	0.29	-0.08	0.54**	0.21	0.18	0.06	0.15
PET			1.00	0.32	0.18	0.46*	0.44*	0.66**	0.21
GAM				1.00	0.26	0.26	0.16	0.39*	0.43*
MAM					1.00	0.26	-0.03	-0.18	0.20
RT						1.00	0.24	0.43*	0.35
LE							1.00	0.45*	0.48*
SH								1.00	0.24
PH									1.00

*p<0.05, **p<0.01

Input-Oriented CCR Model
Objective function:

$$h_k = \max \left(\sum_{r=1}^{s} u_{rk} Y_{rk}\right)$$

Constraints:

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \leq 0, j = 1, \dots, n$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1$$

$$u_{rk} \geq \varepsilon, r = 1, \dots, s$$

$$v_{rk} \geq \varepsilon, i = 1, \dots, m$$

Input-Oriented CCR Model

Objective function:

$$h_k = \max \left(\sum_{r=1}^{s} u_{rk} Y_{rk}\right) - \mu_0$$

Constraints:

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} - \mu_0 \leq 0, j = 1, \dots, n$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1$$

$$u_{rk} \geq \varepsilon, r = 1, \dots, s$$

$$v_{rk} \geq \varepsilon, i = 1, \dots, m$$

$$\mu_0 : serbest$$

DEA, first introduced by Charnes, Cooper and Rhodes in 1978, is a decision-making tool based on linear programming that measures the relative efficiency of comparable multi-input multi-output units. The following summary outlines the application stages of DEA:[24,28,29]

1. **Identification of DMUs:** In DEA, the alternative units whose efficiency is evaluated are termed DMUs. In general, a DMU is considered to be an entity that is responsible for transforming inputs into outputs, and the performance of which is subject to evaluation. It is imperative that the DMUs are comparable, i.e. consist of units with analogous characteristics.
2. **Determination of input and output variables:** The efficiency scores of the DMUs are obtained by proportioning the input and output variables.It is important that the variables to be used in DEA have a high representativeness of the situation to be measured. However, in order to ensure that the number of variables is not excessive, the exclusion of variables with high correlation strengthens the analysis.
3. **Determination of DEA model:** In DEA, two models are selected according to the orientation of the scale and return to scale.The input-oriented model aims to minimise inputs while maintaining the same level of output, with the focus on efficiency improvements by reducing input consumption.In contrast, the output-oriented model aims to maximise outputs with the same level of inputs, with an emphasis on efficiency improvements by increasing output production. According to the principle of returns to scale, the CCR (Charnes, Cooper and Rhodes) model assumes constant returns to scale, while the BCC (Banker, Charnes and Cooper) model assumes variable returns to scale.
4. **Calculation of efficiency value:** The efficiency values of the DMUs within the framework of the selected variables and DEA model are calculated according to the mathematical formalisation of the models based on the most efficient DMU in terms of input and output variables. Thus, an efficiency value ranging between 0-1 is obtained. While the DMUs with an efficiency value of 1 are efficient, the DMUs with an efficiency value less than 1 are relatively inefficient.
5. **Determination of reference DMUs and idle variables:** The analysis yielded the efficient DMUs that are to be regarded as the benchmark against which the inefficient DMUs can achieve efficiency, in addition to the idle variables that necessitate enhancement. Furthermore, the frequency with which the efficient DMUs are referenced has been determined.
6. **Interpretation of the results:** The DMUs' efficiency, the variables employed, the data source, and the research model influence the outcomes of the analysis. It is imperative to interpret the findings obtained from the analysis by taking these criteria into consideration.

RESULTS

The study has evaluated the medical device utilisation efficiency of OECD countries. Table 2 provides a descriptive account of the input and output variables. The mean values of the input variables are as follows: CT mean 28.70, MRI mean 19.38, PET mean 2.58, GAM mean 9.87, MAM mean 23.40 and RT mean 8.02. The mean values for the output variables are 80.45 for LE, 68.25 for SH and 69.88 for PH.

Table 2. Descriptive statistics of variables

	CT	MRI	PET	GAM	MAM	RT	LE	SH	PH
Mean	28.70	19.38	2.58	9.87	23.40	8.02	80.45	68.25	69.88
Median	23.46	17.07	2.04	6.86	16.53	7.31	81.50	68.00	70.10
Std. deviation	14.44	9.67	1.74	9.29	19.12	3.37	2.72	11.87	10.30
Minimum	9.65	5.35	0.71	2.22	3.90	2.75	74.50	44.00	48.10
Maximum	72.37	37.98	8.80	48.76	73.83	18.42	83.20	90.00	88.00

Table 3 shows the efficiency scores of the DMUs according to the input-oriented CCR and BCC models. According to the CCR model, Canada, Czechia, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland and Türkiye are efficient. Accordingly, the efficiency scores of the countries vary between 0.34-1.00 and the average score is 0.86. According to the BCC model, Australia, Austria, Belgium, Canada, Czechia, Denmark, Estonia, Hungary, Iceland, Iceland, Ireland, Israel, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Slovenia, Spain, Sweden, Türkiye and US are efficient countries. Accordingly, countries' efficiency scores range from 0.83 to 1.00 and the average score is 0.98. The scale efficiency scores range from 0.34 to 1.00 and the average is 0.87. In this respect, Canada, Czechia, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland and Türkiye are efficient countries. The countries with the lowest efficiency score are US according to the CCR model, Greece according to the BCC model and US according to the scale efficiency model. In terms of returns to scale, Slovak Republic has increasing returns; Australia, Austria, Belgium, Belgium, Denmark, Finland, Greece, Iceland, Italy, Korea, Norway, Slovenia, Spain, Sweden and US have decreasing returns; Canada, Czechia, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland and Türkiye have constant returns. In a country with increasing returns to scale, a unit increase in inputs leads to a greater increase in output, whereas in countries with decreasing returns to scale, a unit increase in inputs leads to a smaller increase in output. With constant returns to scale, the increase in inputs and outputs is realised at the same level.

Table 3. Efficiency scores according to input-oriented CCR and BCC models

DMUs	CCR efficiency scores	BCC efficiency scores	Scale efficiency (CCR/BCC)	Direction of returns to scale
Australia	0.59	1.00	0.59	drs
Austria	0.78	1.00	0.78	drs
Belgium	0.73	1.00	0.73	drs
Canada	1.00	1.00	1.00	crs
Czechia	1.00	1.00	1.00	crs
Denmark	0.73	1.00	0.73	drs
Estonia	1.00	1.00	1.00	crs
Finland	0.76	0.86	0.88	drs
Greece	0.81	0.83	0.97	drs
Hungary	1.00	1.00	1.00	crs
Iceland	0.86	1.00	0.86	drs
Ireland	1.00	1.00	1.00	crs
Israel	1.00	1.00	1.00	crs
Italy	0.50	0.89	0.57	drs
Korea	0.58	1.00	0.58	drs
Latvia	1.00	1.00	1.00	crs
Lithuania	1.00	1.00	1.00	crs
Luxembourg	1.00	1.00	1.00	crs
Netherlands	1.00	1.00	1.00	crs
New Zealand	1.00	1.00	1.00	crs
Norway	0.87	1.00	0.87	drs
Poland	1.00	1.00	1.00	crs
Slovak Republic	0.95	0.97	0.98	irs
Slovenia	0.99	1.00	0.99	drs
Spain	0.75	1.00	0.75	drs
Sweden	0.84	1.00	0.84	drs
Türkiye	1.00	1.00	1.00	crs
US	0.34	1.00	034	drs
Mean	0.86	0.98	0.87	

DRS: Decreasing returns to scale, CRS: Constant returns to scale, IRS: Increasing returns to scale

Table 4 shows the frequency of referencing of efficient DMUs and the DMUs expected to be referenced by inefficient DMUs according to the input-oriented CCR and BCC models. Looking at the frequency of referencing efficient DMUs to inefficient DMUs, according to the CCR model, Türkiye was referenced 12 times, Canada 10 times, Poland 7 times, Lithuania 5 times, Netherlands 5 times, Luxembourg 4 times, New Zealand 4 times, Canada 3 times, Latvia 2 times and Hungary 1 time. In terms of which efficient countries inefficient DMUs should refer to in order to become efficient, it is recommended that US, which has the lowest efficiency score, should refer to Canada, Israel and Poland. Slovenia, which is the closest to being efficient, can look to Hungary, Israel, Lithuania, Luxembourg and Poland to become efficient. According to the BCC model, Ireland, Israel and New Zealand are referenced twice, and Canada, Lithuania, Netherlands, Sweden and Türkiye once each. When analysing the countries to which inefficient DMUs should refer in order to become efficient, Greece, which has the lowest efficiency score, should refer to Canada, Lithuania and New Zealand.

Table 5 presents the idle values of the variables to be improved by inefficient DMUs according to the input-oriented CCR and BCC models. According to the CCR model, Australia and Slovak Republic CT and RT; Belgium CT, GAM, MAM and RT; Denmark CT, PET and RT; Finland MRI, PET, MAM and RT; Greece CT, MRI, GAM and MAM; Norway, Iceland CT, MRI and RT; Austria, Italy, Sweden and Korea CT, MRI and MAM; Slovenia and Spain MRI, MAM and RT; US MRI, PET, GAM and MAM. According to the BCC model, Finland should make improvements in MRI, PET, MAM and RT; Greece in CT, MRI, GAM and MAM; Italy in CT, MRI, PET and MAM.

Table 4. Reference (Ref.) groups according to CCR and BCC models

DMUs		CCR		BCC	
		Ref. frequency	Ref. DMUs	Ref. frequency	Ref. DMUs
1	Australia		13(0.89), 19(0.13), 22(0.09), 27(0.07)		
2	Austria		13(0.65), 16(0.12), 17(0.01), 27(0.38)		
3	Belgium		13(1.01), 17(0.01), 18(0.17)	1	
4	Canada	3		1	
5	Czechia				
6	Denmark		13(0.97), 19(0.09), 27(0.01)		
7	Estonia				
8	Finland		13(0.34), 27(0.68)		12(0.42), 13(0.27), 19(0.04), 27(0.27)
9	Greece		4(0.42), 17(0.27), 20(0.32)		4(0.40), 17(0.17), 20(0.43)
10	Hungary	1			
11	Iceland		19(0.15), 22(0.39), 27(0.60)		
12	Ireland			2	
13	Israel	10		3	
14	Italy		4(0.01), 20(0.08), 22(0.02), 27(0.96)		12(0.02), 13(0.07), 20(0.25), 26(0.66)
15	Korea		16(0.13), 17(0.01), 20(0.04), 27(0.97)		
16	Latvia	2			

Table 4. Continued

17	Lithuania	5		1	
18	Luxembourg	4			
19	Netherlands	5		3	
20	N. Zealand	4		3	
21	Norway		18(0.03), 19(0.20), 27(0.92)	1	
22	Poland	7			
23	Slovak R.		13(0.33), 20(0.04), 22(0.40), 27(0.20)		
24	Slovenia		10(0.03), 13(0.43), 17(0.16), 18(0.18), 22(0.21)		
25	Spain		13(0.26), 22(0.15), 27(0.65)		
26	Sweden		13(0.04), 18(0.17), 19(0.14), 22(0.09), 27(0.62)	2	
27	Türkiye	12		1	
28	US		4(0.37), 13(0.45), 22(0.31)		

Table 5. Improvement values according to CCR and BCC models (idle input ratio)

DMUs	Idle input ratio											
	(CCR model)						(BCC model)					
	CT	MRI	PET	GAM	MAM	RT	CT	MRI	PET	GAM	MAM	RT
Australia	28.71					1.87						
Austria	5.08	10.39			1.16							
Belgium	4.99			8.15	12.93	7.59						
Denmark	20.45		4.20			3.72						
Finland		15.37	0.85		14.30	4.92		16.04	1.16		16.15	3.10
Greece	12.15	14.98		4.17	40.65		11.72	15.48		4.74	41.88	
Iceland	17.42	6.08				1.54						
Italy	1.28	3.61			5.36		8.51	12.04	1.13		17.38	
Korea	4.00	7.50			26.55							
Norway	7.60	13.06				5.72						
Poland												
Slovak Republic	1.78					6.55						
Slovenia		5.58			3.79	0.56						
Spain		4.71			1.77	1.63						
Sweden	1.66	0.89			0.70							
US		3.11	0.04	6.23	9.55							

DISCUSSION

Medical devices are essential for the diagnosis, prevention, monitoring and medical treatment of diseases and for improving the quality of life of people with health problems. They support evidence-based practice/medicine and effective decision-making in terms of patient care in healthcare institutions30. In addition to their positive impact on health status, the fact that medical devices are expensive investments is seen as a reason for the increase in health expenditure[17]. Although there is a set of standards for the production and use of medical devices6, the unnecessary use of devices can lead to various problems such as idle capacity, increased service delivery costs, and unbalanced distribution of limited resources. Medical equipment should be appropriately managed to fulfill its purpose. The first step to take is to evaluate the current situation; in other words, it is essential to examine whether the existing medical devices are being used effectively.

The efficiency of the use of medical devices was assessed in OECD countries using health outcomes, in 13 countries (Canada, Czechia, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Poland and Türkiye) according to the input-oriented CCR model and 24 (Australia, Austria, Belgium, Canada) according to the BCC model, Czechia, Denmark, Estonia, Hungary, Iceland, Iceland, Ireland, Israel, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Slovenia, Spain, Sweden, Türkiye and US). Countries with inefficient use of medical devices in terms of health outcomes are Australia, Austria, Belgium, Denmark, Finland, Greece, Iceland, Italy, Korea, Norway, Slovak Republic, Slovenia, Spain, Sweden and US according to the CCR model; Finland, Greece, Italy and the Slovak Republic according to the BCC model. In the literature there are studies in support of the research findings as well as studies with different findings[15]. A plethora of factors, including varying regulatory frameworks, infrastructural disparities, the training of healthcare professionals, and economic conditions, have been identified as crucial determinants of the effectiveness of medical devices across diverse geographical regions. High-income countries benefit from advanced systems and strict regulations that increase the use of medical devices, while low and middle income countries struggle with operational inefficiencies that limit their ability to fully utilise these vital health Technologies[31,32]. Conversely, the US, a nation that has historically dominated the global medical device market due to its advanced technological capabilities and substantial R&D investments[3,33], has been found to have a notably low effectiveness score according to the CCR model. A examination of the available data has revealed that this phenomenon can be attributed to the high number of medical devices per capita. In this section, particular attention must be directed towards the mathematical structure of DEA and the selection of variables. DEA employs an approach that prioritises achieving maximum output with minimum input. This may explain the ineffectiveness of the US' position in the medical device market. Furthermore, it is important to note that the effectiveness of DEA is influenced by the variables utilised. The present study demonstrates the effectiveness of medical device use within the framework of CT, MRI, PET, GAM, MAM, and RT input variables, as well as LE, SH, and PH output variables. The effectiveness of countries may vary depending on the variables employed in the DEA. Despite the existence of a mathematical basis for variable selection in DEA[21], it is essential to consider data diversity when evaluating the effectiveness of medical devices across a range of variables. Furthermore, since the quality of healthcare services (e.g., quality of care, patient satisfaction) cannot be directly measured in the analysis, the quality dimension has been disregarded. These limitations may restrict the generalizability of the findings. In subsequent studies, incorporating more comprehensive sets of variables and quality indicators will facilitate overcoming these limitations.

The present study found that Türkiye is effective, a conclusion that has also been confirmed in the literatüre[15]. Despite Türkiye lagging behind other countries in terms of the number of devices, it is first in the number of imaging procedures[18]. The DEA model is predicated on the principle of minimising inputs and maximising outputs. It is hypothesised that Türkiye's superior performance in terms of medical device utilisation, achieved with a smaller number of devices than other countries, is indicative of the efficacy of such technology. İlgün et al.[16] state in their study that medical imaging equipment is used efficiently in 22 out of 81 provinces in Türkiye and that this situation is influenced by the number of physicians and the dependency ratio of the elderly. Sonğur and Top[30], emphasize that there are inequalities in medical devices according to regions and hospital types in Türkiye. Compared to the capacity of medical devices in urban areas of Türkiye, the capacity in rural areas is relatively low[16]. In a study comparing imaging devices in Türkiye based on ownership, it was found that the utilisation of medical imaging devices was relatively high in Ministry of Health hospitals18.

DEA provides findings on the relative effectiveness or ineffectiveness of the DMUs evaluated. However, it is not possible to directly rank the efficient DMUs in terms of their success. In such cases, MCDM techniques may be utilised to calculate efficiency scores and enable performance ranking from best to worst. Indeed, the application of MCDM techniques is widely adopted in the health sector to evaluate the efficiency of different units[34,35]. Furthermore, conducting cost-effectiveness analyses for effective medical device management would be advantageous[36]. DEA also determines the extent to which inefficient DMUs should be used as a reference to become efficient. Accordingly, Türkiye, Israel and Poland are found to be the most referenced among the efficient DMUs. It can be assumed that Türkiye, the countries with the highest number of references, uses medical devices relatively more efficiently. Statistical analysis and research consistently demonstrate that Türkiye holds the global lead in terms of the number of examinations conducted, despite having a comparatively limited number of medical devices in relation to other nations[18,37]. At this point, the unnecessary use of medical devices comes to the fore. If we consider the periods when medical equipment is not used in Türkiye, such as public and administrative holidays, it is clear that the equipment is not used to its full capacity. However, the high number of tests performed raises questions about the necessity of such testing[37]. At this point, planning for the appropriate use of resources by avoiding unnecessary demand becomes important. To this end, it will be useful to avoid unnecessary tests, to ensure full capacity utilisation by using existing equipment during off-hours, and thus to avoid increasing the number of devices.

DEA identifies which input and output variables the inefficient countries should improve in order to become efficient. Since it is difficult to intervene in outputs in the health sector, and attempts to increase outputs may cause ethical problems, it makes more sense to improve inputs. The input variables most in need of improvement are MRI, CT and MAM. The increased utilisation of CT and MRI scans has been demonstrated to result in escalating costs and a concomitant decline in relative efficiency within the healthcare system[19]. Input-oriented DEA is based on the minimum use of inputs for efficiency. Accordingly, it determines the idle input ratios of the DMUs relative to output and recommends improvements in idle inputs. However, the impact of unnecessary use of medical devices cannot be ignored. For example, the unnecessary use of diagnostic tests in the US has reached 24.9 percent[38]. This increases unnecessary healthcare use and therefore healthcare spending. It is estimated that approximately 30 percent of annual healthcare spending is due to unnecessary services[39]. Overutilisation not only increases healthcare costs, but also increases adverse health outcomes, including increased morbidity and mortality[40]. It is important to evaluate the effectiveness of medical devices by taking unnecessary use into account. The unnecessary use of medical devices in inactive countries must be prevented. This will prevent unnecessary examinations, ensure that existing devices are sufficient for service provision, and prevent devices from becoming idle.

CONCLUSION

In conclusion, according to all models, Canada, the Czech Republic, Estonia, Hungary, Ireland, Israel, Latvia, Lithuania, Luxembourg, the Netherlands, New Zealand, Poland, and Türkiye were found to be relatively effective in terms of medical device use. Türkiye, Israel, and Poland were found to be the countries most frequently referenced. Conversely, Finland, Greece, Italy, and the Slovak Republic were found to be ineffective. MRI, CT, and MAM are the input variables that require the most improvement. It is therefore recommended that unnecessary use of medical devices be reduced and existing devices be used more efficiently in these countries. It is worth noting that the activity scores used in this study may be sensitive to the specific input and output variables selected. The potential impact of variable selection on the outcomes is a significant limitation of the study. Therefore, using different sets of variables in future studies will enable the findings to be compared and increase the generalisability of the results. MCDM techniques, which also enable performance ranking, are recommended for studies aiming to measure the effectiveness of medical devices. Given that medical devices are expensive investments and costs are increasing, the financial aspect of these devices becomes more prominent, and it would be helpful to evaluate their financial efficiency.

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