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Evaluation of the Efficiency of Long-Term Care Services in OECD Countries by DEA Method

OECD Ülkelerinde Uzun Süreli Bakım Hizmetlerinin Verimliliğinin DEA Yöntemi ile Değerlendirilmesi

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ABSTRACT

Objective: This research aims to measure the efficiency of health services by using health indicators of OECD countries, to determine inefficiencies of countries that are not at the efficient border, to calculate idle use, and to determine super-efficiency values of countries at active borders.
Methods: In the research, DEA was conducted using an input-oriented CCR model to measure the performance of the OECD countries in 2019, the last year before the pandemic. In the research, three input and two output variables were used. R Studio package programs were used for the analysis of research data.
Results: It is seen that the productivity average of 15 countries is 0.81. 5 out of 16 countries have been identified as active. Finally, it has been determined that Hungary, with a super-efficiency value of 17.18, can still be on an efficient border even if it increases its input amounts 16 times.
Conclusion: A notable observation is that some OECD countries with developed economies allocate substantial resources to long-term care services, and their capacities are at sufficiently high levels. It is recommended that low-productivity countries should reduce the idle use of input resources to increase their productivity.
Keywords: Data envelopment analysis, efficiency, long-term care service, OECD countries

ÖZ

Amaç: Bu araştırma, OECD ülkelerinin sağlık göstergelerini kullanarak sağlık hizmetlerinin verimliliğini ölçmeyi, etkin sınırda olmayan ülkelerin verimsizliklerini belirlemeyi, kullanılmayan kaynakları hesaplamayı ve etkin sınırda olan ülkelerin süper-verimlilik değerlerini belirlemeyi amaçlamaktadır.
Yöntemler: Araştırmada, OECD ülkelerinin performansını ölçmek için 2019, pandemiden önceki son yıl, giriş odaklı CCR modeli kullanılarak veri zarflama analizi yapılmıştır. Araştırmada üç girdi ve iki çıktı değişkeni kullanılmıştır. Araştırma verilerinin analizi için R Studio paket programları kullanılmıştır
Bulgular: 15 ülkenin verimlilik ortalamasının 0,81 olduğu görülmektedir. 16 ülkeden 5'i etkin olarak belirlenmiştir. Son olarak, 17,18 süper-verimlilik değerine sahip Macaristan'ın, girdi miktarlarını 16 kat arttırsa bile etkin sınırda kalabileceği belirlenmiştir.
Sonuç: Gelişmiş ekonomilere sahip bazı OECD ülkelerinin, uzun süreli bakım hizmetlerine önemli kaynaklar ayırdığı ve kapasitelerinin yeterince yüksek seviyelerde olduğu görülmüştür. Düşük verimliliğe sahip ülkelerin, verimliliklerini artırmak için girdi kaynaklarının kullanılmayan miktarlarını azaltmaları önerilmektedir.
Anahtar Kelimeler: Veri zarflama analizi, verimlilik, uzun süreli bakım hizmeti, OECD ülkeleri

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Introduction

In recent years, the elderly population, which constitutes a significant portion of the population, has been increasing faster than expected. The population pyramid of many developed countries confirms the increase in the elderly population (OECD, 2021a). This increase is projected to continue in the coming decades. In OECD countries, the percentage of people aged 80 years and over is projected to double from 4% in 2010 to nearly 10% in 2050 (Colombo et al., 2011). Population aging, changing social phenomena, increased female labor force participation, and changes in family structure are vital to helping governments and institutions understand the potential dimensions of the challenge facing long-term care systems and develop policies accordingly (Trigg, 2011).

Long-term care encompasses a diverse range of services that individuals necessitate due to their diminished capacity to perform daily activities independently (Doty and Wiener, 1985). The imperative for long-term care services arises from the escalating prevalence of chronic diseases and the decline in functional capacity and self-care abilities (Barreira et al., 2023). Notably, long-term care has become an increasingly critical concern for OECD countries. Over the past decade, the proportion of the population availing long-term care services has witnessed an upsurge in nearly all OECD nations. According to the European Commission's report on aging, approximately 7% of the global population is projected to require long-term care, with a stark contrast of 19% among individuals aged 65 years and above (European Commission, 2021). Effectively addressing the escalating prevalence of diseases necessitating long-term care stands out as the primary challenge confronting governments and health systems on a global scale (WHO, 2011). Demographic factors, including the burgeoning population of individuals aged 65 years and older, diminished fertility rates, and extended life expectancy, collectively contribute to heightened dependency ratios. These demographic dynamics significantly intensify the demand for both formal and informal long-term care services (Kordić and Višić, 2022).

Long-term care services, increasing due to the aging population, pose labor shortage problems in developed and developing countries. To sustain the existing ratio of five long-term care workers for every 100 individuals aged 65 and over across OECD countries, the workforce in the sector would need to expand by 13.5 million by the year 2040 (OECD, 2021b). Enhancing comprehension of the present demand and supply dynamics in long-term care is imperative for informing strategic policy planning, judicious resource allocation, and fostering workforce empowerment. These insights are crucial for the development of an efficacious and sustainable long-term care system capable of adeptly addressing the requirements arising from an aging population (Feng et al., 2020). In addition to labor, one of the main inputs, capital investment in long-term care services is known to require substantial resources, especially as it is needed in every country's urban and rural areas of every country14. Government and private market spending on long-term care services account for 1.5% of GDP across the OECD and is projected to double or even triple between now and 2050 (Colombo et al., 2011). Across OECD countries, the combined expenditure on health and long-term care is projected to increase by 3.3 and 7.7 percentage points of GDP between 2010 and 2060 in the cost-containment and cost-pressure scenarios, respectively (de la Maisonneuve and Oliveira Martins, 2014).

Given the implications of long-term care, demographic shifts, evolving expectations regarding the scale and quality of services, the anticipated integration of new technologies in the forthcoming years, and economic pressures on welfare states, numerous countries globally are directing their attention toward formulating new policies and strategies in this domain. Additionally, research studies are being undertaken to further explore and address these multifaceted challenges (Greve, 2017). In the study conducted by Ariaans et al. (2021), an innovative and updated typology for Long-Term Care (LTC) is presented, which, overall, contributes to our understanding of the structure and design of various LTC systems. The conclusion suggests that this typology may be of interest to policymakers in the LTC field who grapple with the challenges posed by aging societies. Due to the nature of long-term care services, some studies have used health indicators such as the number of beds, long-term care workers, and long-term care service users (Luasa vd., 2018; Wu et al., 2021). While research in this field emphasizes the productivity and efficiency of the long-term care sector, there is notable variation in the samples utilized. The majority of studies tend to concentrate on long-term care services within the context of a single country, with only a limited number of studies conducting international comparisons. This study analyzes the efficiency of long-term care resources and utilization in OECD countries within the scope of the variables used. The data envelopment analysis (DEA) method evaluates the efficiency of long-term care services. In this research, the main motivation of the research is to help policy makers to develop a long-term transport system that meets the expectations of the society with high quality and low cost.

Conceptual Framework

Data Envelopment Analysis, which is based on M.J. Farrell's work in 1957, was first developed by Charnes, Cooper and Rhodes (1978) as a method to evaluate the comparative efficiency of organisational units (Olariu and Brad, 2017). DEA technique has undergone a rapid development both theoretically and practically in the following times. Initially, efficiency measurements were made only in the service areas of public institutions with the assumption of constant returns to scale. By 1984, the BBC model was developed and the variable returns to scale and scale and technical efficiencies could be measured separately. Subsequently, multiplicative, non-directional, aggregative etc. models were developed and new models are still being developed (Baysal et al., 2005; Dikmen, 2007).

DEA, or Data Envelopment Analysis, is a method rooted in data to evaluate the performance of a group of entities known as Decision Making Units (DMUs). These DMUs are entities that transform various inputs into multiple outputs. The definition of a DMU is broad and adaptable, as outlined by Cooper et al. in 2011. DEA is a technique based on linear programming used to measure the performance efficiency of organisational units, referred to as DMUs. DEA aims to measure the extent to which a DMU uses available resources efficiently to produce a set of outputs. DMUs can refer to production units, universities, schools, bank branches, hospitals, tax offices, defence bases and even practitioners such as doctors and nurses (Ramanathan, 2003).

While DEA has some advantages, it also has some weaknesses. The most important advantage of DEA is that it can be applied to multiple inputs and multiple outputs at the same time, while its weakest point is that it is very sensitive to variable selection and data errors (Kalirajan and Shand, 1999). The advantages of DEA can be listed as follows (Arnade, 1994; Bowlin, 1987; Jenkins and Anderson, 2003; Rouyendegh, 2009);

- Data Envelopment Analysis (DEA) provides a method for the simultaneous evaluation of multiple input and output variables within Decision Making Units (DMUs).

- DEA allows the analyser to recognise the input and output variables used in the analysis.

- DEA enables the comparison of the performance of Control Variable Bounds (CVBs) with similar characteristics.

- Due to its lack of requirement for a predetermined functional form between input and output variables, DEA possesses a more flexible structure compared to parametric methods.

- Given the flexibility of expressing input and output variables in diverse units within DEA, the efficiency of Decision Making Units (DMUs) can be assessed from various perspectives.

- As a result of DEA, it contributes to the development of the managerial activities of the enterprises by guiding the efficient state of the CVBs that are not on the efficient frontier.

In addition to its superior aspects, DEA also has some weaknesses. The weaknesses of DEA can be listed as follows (Smith, 1997; Kutlar and Bakırcı, 2018; Easton et al., 2002);

- Since DEA is a nonparametric method, it is not possible to apply statistical analyses to test whether the selected model is appropriate.

- Input and output variables with very large or small values included in the analysis in DEA make it difficult to form the relative efficiency frontier.

- Failure to include an important variable in DEA in terms of KVBs in the analysis may cause the analysis to give misleading results.

- In instances where the count of Control Variable Bounds (CVBs) included in the research is inadequate, falling short of the sum of the number of inputs and outputs, the analysis may yield unreliable results.

- DEA is very sensitive to measurement errors in the calculation of input and output variables.

In DEA method, basically two models, namely CCR and BCC models, are used. If the efficiency analysis is to be performed with the assumption of constant returns to scale, CCR model is used, and if it is to be performed with the assumption of variable returns to scale, BCC model is used. In addition, each model is divided into two as input and output orientated.

Developed in 1978 by Charnes, Cooper, and Rhodes, the CCR (Charnes, Cooper, and Rhodes) model stands as the foundational and initial DEA model. The model, which works on the basis of the assumption of constant returns to scale, can determine the source and amount of inefficiency by calculating the total efficiency values of the CVBs (Charnes et al., 1978). In order for a CVB to be efficient in the CCR model, it must be efficient both in terms of technical efficiency and scale efficiency. The input-oriented CCR model is used when there is little or no control over output variables. In input-oriented models, the objective is to spend the minimum amount of input to produce the potential amount of output. In output-oriented models, on the other hand, the objective is to produce the maximum output set with a certain set of inputs (Dinç and Haynes, 1999). In other words, in input-oriented models, the minimum amount of input is used to produce the available output, while in output-oriented models, the maximum amount of output is produced with the available input (Charnes et al., 1978).

Formulated in 1984 by Banker, Cooper, and Charnes as an alternative to the CCR model, the BCC (Banker, Cooper, and Charnes) model operates under the assumption of variable returns to scale (Banker et al., 1992). The BCC model can determine the source and amount of inefficiency by measuring the technical efficiency of CVBs. While the total efficiency of CVBs can be measured with the CCR model, technical efficiency can be measured with the BCC model (Cooper et al., 2007). As in input-oriented CCR models, input-oriented BCC models determine the most appropriate input combination that should be used in order to produce an efficient output combination in the most efficient way. In input-oriented BCC models, the objective is to attain the efficient frontier by proportionally reducing inputs. Conversely, in output-oriented BCC models, similar to output-oriented CCR models, the goal is to maximize outputs without altering the allocated resources, aiming to reach the efficient frontier (Charnes et al., 1978).

Methods

In the study, DEA was conducted using the input-oriented CCR model to measure the performance of OECD countries in 2019, the last year before the pandemic. In the study, the number of nurses per 100 people over 65, the number of caregivers per 100 people over 65, and the ratio of long-term care expenditures to health expenditures were used as input variables. In contrast, the ratio of those receiving long-term care services at home in the population over the age of 65 and the ratio of those receiving long-term care services in care institutions in the population over the age of 65 were used as output variables. The selection of input and output variables was guided by insights derived from the existing literatüre (Çilhoroz and Arslan-Çilhoroz, 2022; Demirci et al., 2020; Luasa et al., 2018; Wu et al., 2021), particularly drawing upon information available in the "Health at a Glance 2021" report published by the OECD. This reputable source (OECD, 2021b) provides comprehensive and up-to-date data on various aspects of health systems, including those related to the elderly population and Long-Term Care (LTC) services. Among 37 OECD countries, 16 countries with complete data were included in the analysis. Data from the OECD database were used in the study. R Studio package programs were employed for the analysis of the research data. Subsequently, the outcomes of the package programs were transferred to the Excel software for tabulation, and the acquired results were discussed in the application section.

This research aims to measure the health service efficiency of OECD countries by using health indicators to identify the source of inefficiency of countries that are not on the efficient frontier, to calculate their idle utilization, and to determine the super-efficiency values of countries on the efficient frontier.

As we utilized publicly available secondary data in our study, ethical committee approval is not required. The data has been obtained from previously collected sources that are openly accessible. This circumstance demonstrates that the study has been conducted in accordance with current ethical standards and regulations, and there is no necessity for obtaining ethical committee approval.

Results

This section presents the results of DEA analysis with the input-oriented CCR model using the 2019 data of 15 countries.

First, domestic and foreign sources were reviewed, and the variables frequently used in the literature were determined. Then, Spearman correlation analysis was applied as a preliminary analysis to measure the relationship between the variables. The results of the Spearman correlation analysis between the variables show that the highest correlation between the three input and two output variables used in the research is 0,488. The lower the correlation between the variables used in DEA analysis, the more comprehensive and accurate analysis results will be possible. In this context, using variables with high correlation in DEA analyses is avoided. The fact that many of the variables used in the study have very weak correlations is of great importance in this respect.

After Spearman correlation analysis, it was decided to use input and output variables with low correlation in the research.

When the input variables of the 16 countries are examined, it is seen that the average number of nurses per 100 people over the age of 65 is 1,5, the average number of caregivers per 100 people over the age of 65 is 5, and the average ratio of long-term care expenditures in health expenditures is 16.

Regarding output variables, the average ratio of those receiving long-term care services at home in the population over 65 years of age is 9.9, and the average ratio of those receiving long-term care services in care institutions over 65 years of age is 3.9. The country with the highest number of nurses per 100 people over 65 is Switzerland; the country with the highest number of caregivers per 100 people over

65 is Sweden; the country with the highest ratio of long-country with the highest ratio of long-term care services in care facilities to the population over 65 in Australia. As seen in Table 1 above, the Mahalanobis test was applied to identify countries with outlier values.

Table 1.
Mahalanobis and Chi-square Values for Countries

Countries	Mahalanobis Value	Chi-Square Value
Australia	5.5	0.23
Estonia	3	0.55
Hungary	3.8	0.43
Israel	11.6	0.02
South Korea	1.6	0.79
Luxembourg	1.8	0.76
Netherlands	3.1	0.53
Norway	8.9	0.06
Portugal	8.5	0.07
Sweden	5.2	0.26
Switzerland	8.4	0.07
Canada	5	0.28
Denmark	1.2	0.86
Germany	4	0.39
New Zealand	1.2	0.87
U.S.A.	1.6	0.80

Table 2.
CCRInput Oriented Efficiency Results of the Countries Included in the Analysis

Countries	Event Results
Australia	0.98
Estonia	1
Hungary	1
South Korea	1
Luxembourg	0.66
Netherlands	0.49
Norway	0.37
Portugal	1
Sweden	0.78
Switzerland	0.59
Canada	1
Denmark	0.73
Germany	0.89
New Zealand	0.91
U.S.A.	0.84
AVERAGE	0.81

Countries with high Mahalanobis values were identified, and countries with Chi-Square values at the significance level ($p<.05$) were excluded from the study. For this reason, Israel, with a Mahalanobis value of 11.6 and a Chi-Square value of 0.02, was excluded from the study, and 15 countries were included in the analysis

Table 2 above shows the CCR input-oriented efficiency results of the countries. The average score obtained as a result of the analysis of the data of these countries in 2019 with the CCR model was determined as 0.81. 5 out of 16 countries were found to be efficient. Among the 16 countries, Norway has the lowest efficiency with an efficiency ratio of 0.37. Moreover, among the inefficient countries, the country with the highest efficiency is Australia with an efficiency ratio of 0.98. Finally, according to the efficiency scores, there are 2 countries below 0.50, 2 countries between 0.50-0.70, 2 countries between 0.71-0.80, 2 countries between 0.81-0.90 and 2 countries above 0.91. As shown in Figure 1 above, Hungary was referenced ten times, Estonia 9 times, South Korea 6 times, Portugal 2 times, and Canada 1 time. In total, it is seen that inefficient countries reference all of the five countries identified as efficient.

Table 3.
Countries that Inefficient Countries Should Reference

Countries	Estonia	South Korea	Canada	Hungary	Portugal
Australia	0.87	0	0	0.65	0
Luxembourg	0.53	0	0	0.57	0
Netherlands	0.32	0	0.37	0.22	0.52
Norway	0.26	0.40	0	0.75	0
Sweden	0	0.78	0	0.04	0
Switzerland	0.10	0.29	0	0	0
Denmark	0.14	0.94	0	0.42	0
Germany	0	0.67	0	0	0
New Zealand	0.72	0.45	0	0.14	0
U.S.A.	0.45	0	0	0.61	0

The countries that inefficient countries need to reference to become efficient are shown in Table 3 above. Norway, which has the lowest efficiency, needs to reference Hungary 75%, South Korea 40%, and Estonia 26% in order to become efficient. Similarly, the Netherlands, another country with low efficiency, needs to reference Portugal 52%, Canada 37%, Estonia 32%, and Hungary 22% to be efficient. Finally, it is seen that countries with low efficiency generally take Estonia as a reference.

Table 4. Efficiency Goals of Inefficient Countries			
Countries	Number of nurses	Number of caregivers	Health expenditures
Australia	1.37	4.61	10.9
Luxembourg	1.45	3.37	12.5
Netherlands	1.08	2.81	13.8
Norway	1.45	3.12	11
Sweden	0.55	8.81	20.7
Switzerland	3.01	1.95	12
Denmark	0.96	4.65	15.7
Germany	1.97	2.87	13.5
New Zealand	0.54	5.64	13.4
U.S.A.	1.17	2.44	6.8

In Table 4 above, the values that inefficient countries should bring their input resources in order to become efficient are given. On the other hand, since the target and current inputs of the countries on the efficient frontier are the same, the values of the efficient countries are not given in Table 4. It is believed that the main reason the countries below the efficient frontier are inefficient is that they cannot achieve the expected output with their current input resources, and this is supported by the fact that they have diminishing returns to scale. Norway, the country with the lowest efficiency, idles about 2/3 of its input resources; the Netherlands, the country with the second lowest efficiency, idles almost half of its input resources and Switzerland, the country with the third lowest efficiency, idles about 35% of its input resources.

Scale efficiency is used to determine the increase, decrease, and constant per unit. Scale efficiency, which refers to production at the most appropriate scale, is calculated by dividing the results obtained with the CCR model by those obtained with the BCC model. The increase, decrease, and constancy situations resulting from the return-to-scale results of the countries' data for 2019 are expressed in Table 5 below. As stated in (Banker & Thrall, 1992), the efficiency results in Table 5, where returns to scale are expressed, can be interpreted as constant returns if equal to 1, decreasing returns if greater than 1, and increasing returns if less than 1.

When the scale efficiency results in Table 5 are analyzed, it is found that out of 15 countries, five countries have constant returns to scale, and ten countries have decreasing returns to scale. There is no country with increasing returns to scale. Accordingly, to be efficient, countries with decreasing returns to scale should increase their output by keeping their inputs constant instead of increasing their inputs.

Table 5. Returns to Scale Results for the Countries Included in the Analysis		
Countries	Return to Scale Result	Returns to Scale Type
Australia	1.53	Declining
Estonia	1	Fixed
Hungary	1	Fixed
South Korea	1	Fixed
Luxembourg	2.15	Declining
Netherlands	1.45	Declining
Norway	1.43	Declining
Portugal	1	Fixed
Sweden	1.90	Declining
Switzerland	2.12	Declining
Canada	1	Fixed
Denmark	1.51	Declining
Germany	1.76	Declining
New Zealand	1.32	Declining
U.S.A.	1.07	Declining

In other words, to be efficient, countries with decreasing returns to scale should achieve the same output level with less input. Therefore, according to the return to scale results, the ten inefficient OECD countries should reduce their input resources or produce more output by keeping them constant to achieve efficiency in long-term care services.

Super-efficiency analysis measures the efficiency between units at the efficient level. In this study, the efficiency levels among the five countries at the efficient frontier are given in Table 6 below. Values greater than one indicate how units can increase their inputs without changing their efficiency status.

Table 6. Super Efficiency Values of the Countries Found to be Efficient	
Countries	Event Results
Hungary	17.18
Estonia	1.83
South Korea	1.81
Portugal	1.31
Canada	1.05

Table 6 shows that Hungary has the highest efficiency level among the five countries identified as efficient. With a super efficiency value of 17.18, it is seen that Hungary can still be on the efficient frontier even if it increases its input amounts 16 times. With a super-efficiency ratio of 1.83%, it is seen that Estonia can be at the efficient frontier even if it increases its inputs by 83%.

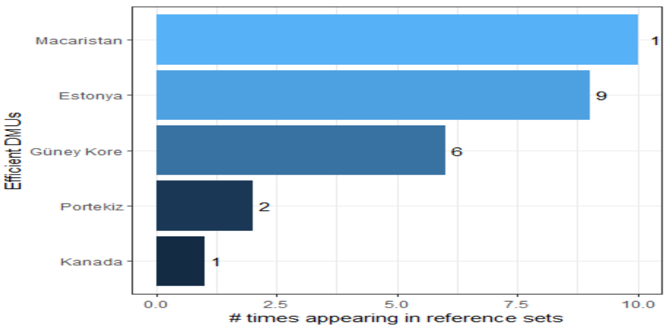

Figure 1. Reference Frequencies of Countries İdentified as Efficient (Effective)

Discussion

In the examination conducted by Puig-Junoy in 2000, the efficiency of 94 acute care hospitals in Spain was assessed utilizing the DEA methodology. Input parameters encompassed the quantification of physicians, nurses, other personnel, and available beds, whereas output variables were represented by the number of discharges and the cumulative days of hospitalization. The computed average efficiency across the hospitals was established at 0.638. This metric serves as a quantitative measure offering insights into the overarching performance of the hospitals, predicated on the designated input and output criteria as subjected to the rigorous analysis facilitated by DEA.

Through the application of the Data Envelopment Analysis (DEA) method, Björkgren, Hakkinen, and Linna (2001) evaluated the efficiency of nursing care in 64 long-term care institutions in Finland. The input variables considered encompassed the count of licensed nurses, registered nurses, auxiliary staff, and available beds. Concurrently, the output variables consisted of the weighted number of days of stay. The research outcome revealed that, in terms of cost efficiency, licensed nurses exhibited the highest efficiency at 66%, followed by registered nurses at 18%, and auxiliary staff at 16%. This delineation provides valuable insights into the relative efficiency of different categories of nursing staff within the context of long-term care institutions in Finland.

Laine et al. (2005) measured technical efficiency and clinical care quality with the DEA method using 2001 data from nursing homes and public hospitals in Finland. They used full-time working years, number of beds, type of institution, and bed occupancy rate for registered nurses, licensed nurses, and auxiliaries as input variables and case-mix weighted patient days as output variables. As a result of the research, they found that technical inefficiency in long-term care services and wards was approximately 15%. They also stated they could not detect a systematic relationship between technical efficiency and clinical care quality.

In their study, Moreno-Serra and Smith (2012) measured the productivity of 79 countries with fully available data between 2000 and 2006 using the DEA method. They used pooled health expenditure per capita, GDP per capita, and primary school education level as input variables and the ratio of out-of-pocket expenditures to total health expenditures, immunization coverage, and the proportion of measles-vaccinated children aged 12-23 months as output variables. As a result of the research, they found 18 countries to be efficient, and they also stated that the average efficiency level was 0.44.

Csakvari et al. (2015) conducted an assessment of the efficiency of long-term care institutions in Hungary spanning the years 2006 to 2013, utilizing the input-oriented DEA method. The input variables in their analysis included the number of beds and the average length of stay, while the output variables encompassed the number of patients discharged, the number of fees paid, and the total number of days. The research findings indicated that the technical efficiency of these institutions was calculated at 94.2% in 2006, 88.6% in 2010, and 95.1% in 2013. The authors further noted that the units exhibited relatively high efficiency values across all the examined years. This analysis contributes valuable insights into the performance dynamics of long-term care institutions in Hungary over the specified time period.

Wichmann et al. (2018) examined the efficiency of long-term care institutions in the EU countries of Belgium, England, Finland, Italy, the Netherlands, and Poland with the output-oriented DEA method. They used staffing and capacity as input variables and maximum quality of life and quality of death as output variables. As a result of the study, they found that Poland and Finland are the most efficient countries when only nurses and nursing assistants are considered as inputs. They also stated that there are significant differences in the efficiency of long-term care institutions within and between countries.

Ozbugday et al. (2019) investigated the efficiency of long-term care services across 17 OECD countries from 2009 to 2014. Their analysis incorporated the total number of beds and expenditures in long-term care institutions as input variables, with the number of patients in long-term care institutions serving as output variables. The study identified Estonia, Hungary, Japan, Poland, Slovakia, and the United States as countries demonstrating efficiency. Additionally, Greece, Poland, and the United States were highlighted as the most frequently referenced nations in the context of long-term care services. This research contributes valuable insights into the comparative efficiency and international referencing patterns within the realm of long-term care across the studied countries.

In their 2022 study, Çilhoroz and Arslan-Çilhoroz employed the Data Envelopment Analysis (DEA) method to assess long-term care efficiency across OECD countries. The study considered input variables such as the proportion of the population aged 65 and over, long-term care expenditures, inadequate physical activity rate, alcohol consumption, smoking rate, and obesity rate. Output variables included the mortality rate among individuals aged 65 and over. The research findings identified Turkey, Sweden, Portugal, Slovakia, Mexico, Korea, Japan, Israel, Iceland, Greece, Finland, and Australia as efficient countries based on the specified input and output variables.

Furthermore, the study situated its findings within the broader context of existing literature. Notable among these references were studies by Yeşilaydın and Alptekin (2016) on the health system efficiency of 34 OECD countries, Şenol et al. (2019) on the comparative health system efficiency of 32 OECD countries and Turkey, Selamzade and Özdemir (2020) on health services efficiency of OECD countries against Covid-19, Kocaman et al. (2012) examining the effectiveness of health systems in 34 OECD countries, Tokatlıoğlu and Ertong (2020) evaluating the effectiveness of health sectors in OECD countries, and Çakmak and Konca (2019) scrutinizing the effectiveness of mental health services in OECD countries. These collective studies contribute to a comprehensive understanding of health service efficiency across OECD nations.

Conclusion

With the aging of the population, many diseases, especially chronic diseases, which require long-term care, are expected to increase significantly. For this reason, increasing the number of long-term care institutions and allocating more resources in the coming years is necessary. With the increase in the services provided in this field, the importance of effective and efficient use of the resources allocated to this field increases even more.

In this context, this study aims to measure health service efficiency by using the health indicators of OECD countries to identify the source of inefficiency of countries that are not on the efficient frontier, to calculate their idle utilization, and to determine the super efficiency values of countries on the efficient frontier. DEA was applied with the input-oriented CCR model using the 2019 data of OECD countries.

As a result, five countries out of 15 countries included in the analysis were found to be efficient. Norway exhibits the lowest efficiency among the countries studied, with an efficiency ratio of 0.37, whereas the average efficiency level is 0.81. A scrutiny of reference frequency reveals that Hungary is the most frequently referenced country, and it is noteworthy that inefficient countries make references to all countries identified as efficient. It is also observed that countries with low efficiency usually take Estonia as a reference. Norway, which has the lowest efficiency, is found to idle 2/3 of its input resources.

In contrast, the Netherlands, which has the second lowest efficiency, is found to idle almost half of its input resources. The returns to scale scores indicate that among the 15 countries studied, 5 exhibit constant returns, while 10 countries display decreasing returns to scale. For countries experiencing decreasing returns to scale, it is advisable to concentrate on optimizing resource utilization by maintaining inputs at a constant level rather than increasing them.

Looking at the super-efficiency results of the efficient countries, it is seen that Hungary is the most efficient country, and even if Hungary increases its inputs 16 times, it can still be on the efficient frontier. Finally, it is noteworthy that none of the 15 OECD countries has increasing returns to scale. This can be interpreted as the fact that OECD countries with developed economies allocate excellent resources to long-term care services, and their capacities are sufficiently high. This study may help develop a high-quality and cost-effective long-term care services system that meets the population's expectations. The most important limitation of the study is that the study covers the year 2019, and future studies using different variables and more up-to-date data will contribute to the literature.

In this way, the study's results can help policymakers develop an appropriate long-term care services system that is low-cost, high-quality, and responsive to the population's expectations. Finally, the results obtained should be evaluated in terms of the variables used in this study, and it is also possible to reach different results with different variables.

This study is subject to certain limitations. Firstly, the efficiency measured using DEA analysis can vary depending on the selected input and output variables. The scope and accuracy of the variables used in the measurement may impact the generalizability of the results. Additionally, the analysis focuses solely on the year 2019 and does not account for the changing conditions post the COVID-19 pandemic, potentially limiting the relevance and applicability of the findings. This study's findings represent a significant stride in evaluating the healthcare efficiency of OECD countries and understanding the effective and efficient utilization of resources in the field of long-term care. Based on the analysis results, we identified five countries as effective in terms of healthcare efficiency. However, Norway's low efficiency ratio indicates that resources in this domain are insufficient and inefficiently utilized. Additionally, policymakers can contribute to the development of a high-quality and cost-effective system in long-term care services. Nevertheless, it is crucial to note that the analysis is subject to specific limitations, and future studies incorporating more recent data and different variables can further enrich the literature.

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Genişletilmiş Özet

Uzun dönemli bakım, demografik değişiklikler, hizmetin büyüklüğü ve kalitesi konusundaki beklentiler, önümüzdeki yıllarda yeni teknolojinin kullanımı ve refah devletleri üzerindeki ekonomik baskı göz önüne alındığında, dünyadaki birçok ülke bu alanda yeni politika ve stratejiler geliştirmek üzerinde odaklanmakta ve çalışmalar yürütmektedir. Yapılan bazı çalışmalarda yatak sayısı, uzun dönemli bakım hizmeti çalışan sayısı, uzun dönemli bakım hizmeti alan kullanıcı sayısı vb. gibi sağlık göstergelerin kullanıldığı görülmektedir. Çalışmalar sektörün üretkenliği ve verimliliğine odaklansa da kullanılan örneklemleri açısından farklılık göstermektedir. Çalışmaların birçoğu yalnızca bir ülkedeki uzun dönemli bakım hizmetlerine odaklanırken, uluslararası kıyaslama yapan çalışma sayısına çok az sayıda rastlanılmıştır. 65 yaş ve üzeri nüfusun artmasına, düşük doğurganlık oranlarına ve yükselen yaşam beklentisine bağlı olarak, OECD ülkelerinde yaşlı nüfusun oranı artmaktadır. OECD ülkelerinde, 65 yaş ve üzeri nüfusun toplam nüfusa oranı 1960 yılında %9 iken, bu oran 2015 yılında %17'ye yükselmiştir. Ayrıca, 2050 yılına gelindiğinde, çoğu OECD ülkesinde nüfusun en az %25'inin 65 yaş ve üzerinde olacağı tahmin edilmektedir. Nüfusun yaşlanmasıyla birlikte, özellikle uzun vadeli bakım gerektiren kronik hastalıkların önemli ölçüde artması beklenmektedir. Bu nedenle, önümüzdeki yıllarda uzun vadeli bakım kurumlarının sayısını artırmak ve daha fazla kaynak ayırmak gereklidir. Bu alanda sunulan hizmetlerin artmasıyla birlikte, bu alana ayrılan kaynakların etkili ve verimli bir şekilde kullanılmasının önemi daha da artmaktadır. Bu araştırma, OECD ülkelerinin sağlık hizmeti verimliliğini ölçmeyi amaçlamaktadır. Sağlık göstergelerini kullanarak etkili sınırda olmayan ülkelerin verimsizlik kaynaklarını belirlemeyi, kullanılmayan kaynaklarını hesaplamayı ve etkili sınırdaki ülkelerin süper-verimlilik değerlerini belirlemeyi hedeflemektedir. Bu kapsamda yapılan çalışmada OECD ülkelerinin uzun dönemli bakım kaynakları ve kullanımının verimlilikleri değerlendirilmiş, ülkeler arasında kıyaslama yapılması, uzun dönemli bakım modellerinin etkilerinin karşılaştırılması yapılmıştır. Bu sayede çalışmadan elde edilen sonuçlar, politika yapıcılar için uzun dönemli bakım hizmetlerinin düşük maliyetli, yüksek kaliteli ve nüfusun beklentilerine yanıt verebilen uygun bir uzun dönemli bakım hizmetleri sistemi geliştirebilmelerine yardımcı olabilecektir. Çalışmada, OECD ülkelerinin 2019 yılındaki performansını ölçmek amacıyla girdi yönlü CCR modeli kullanılarak VZA gerçekleştirilmiştir. Çalışmada, 100 kişi başına düşen hemşire sayısı, 100 kişi başına düşen bakım vericilerin sayısı ve uzun dönemli bakım harcamalarının sağlık harcamalarına oranı girdi değişkenleri olarak kullanıldı. Bunun karşılığında, 65 yaş üstü nüfusta evde uzun vadeli bakım hizmeti alanların oranı ve 65 yaş üstü nüfusta bakım kurumlarında uzun vadeli bakım hizmeti alanların oranı çıktı değişkenleri olarak kullanılmıştır. Analize dahil edilen 37 OECD ülkesi arasında, tam veriye sahip olan 15 ülke ile analize gerçekleştirilmiştir. Veriler OECD veritabanından elde edilmiştir. Araştırma verilerinin analizi için R Studio paket programları kullanılmıştır. Paket programların analiz sonuçları Excel programına aktarılarak, tablolar halinde düzenlenmiş ve elde edilen sonuçlar uygulama bölümünde tartışılmıştır. İlk olarak, yerel ve uluslararası kaynaklar gözden geçirilmiş, literatürde sıkça kullanılan değişkenler belirlenmiştir. Ardından, değişkenler arasındaki ilişkiyi ölçmek için ön bir analiz olarak Spearman korelasyon analizi uygulanmıştır. Araştırmada kullanılan üç girdi ve iki çıktı değişkeni arasındaki Spearman korelasyon analizinin sonuçları sunulmuştur. Araştırmada kullanılan değişkenler arasındaki korelasyon ne kadar düşükse, VZA sonuçlarının daha kapsamlı ve doğru olması mümkün olacaktır. Bu bağlamda, VZA’da yüksek korelasyona sahip değişkenlerin kullanılması önlenir. Çalışmada kullanılan birçok değişkenin çok zayıf korelasyonlara sahip olması, bu açıdan büyük bir öneme sahiptir. Sonuç olarak, analize dahil edilen 15 ülkenin beş tanesi etkili olarak belirlenmiştir. En düşük verimliliğe sahip ülke Norveç'tir ve verimlilik oranı 0,37'dir, bu rakamın karşılaştırıldığı ortalama verimlilik düzeyi ise 0,81'dir. Referans sıklığına bakıldığında, Macaristan'ın en sık referans alınan ülke olduğu görülmekte ve etkisiz ülkelerin genellikle etkili olarak belirlenen ülkeleri referans olarak aldığı görülmektedir. Ayrıca, düşük verimliliğe sahip ülkelerin genellikle Estonya'ya referans olarak aldığı gözlemlenmiştir. En düşük verimliliğe sahip olan Norveç'in, girdi kaynaklarının üçte ikisini verimli olarak harcamadığı tespit edilmiştir. Öte yandan, ikinci en düşük verimliliğe sahip olan Hollanda'nın, girdi kaynaklarının neredeyse yarısını boşa harcadığı gözlemlenmiştir. Ölçek skorları, 15 ülkeden 5'inin sabit getiriye sahip olduğunu, 10 ülkenin ise ölçek getirisinde azalmaya sahip olduğunu göstermektedir. Azalan ölçek getirisi olan ülkeler, girdilerini artırmak yerine sabit tutarak kaynaklarını verimli bir şekilde kullanmaya odaklanmalıdır. Etkili ülkelerin süper-verimlilik sonuçlarına bakıldığında, Macaristan'ın en verimli ülke olduğu görülmekte ve Macaristan'ın girdilerini 16 kat artırsa bile hâlâ etkin sınırdan çıkmayabileceği ortaya çıkmaktadır. Son olarak, 15 OECD ülkesinden hiçbirinin artan ölçek getirisi olmadığı dikkat çekicidir. Bu durum, gelişmiş ekonomilere sahip OECD ülkelerinin uzun vadeli bakım hizmetlerine mükemmel kaynaklar ayırdığını ve kapasitelerinin yeterince güçlü olduğunu gösteren bir gerçek olarak yorumlanabilir. Bu çalışma, nüfusun beklentilerine uygun, yüksek kaliteli ve maliyet-etkin uzun vadeli bakım hizmetleri sistemi geliştirmeye katkıda bulunabilir. Çalışmanın en önemli kısıtlılığı, yalnızca 2019 yılını kapsamasıdır. Farklı değişkenler ve daha güncel veriler kullanılarak yapılacak gelecekteki çalışmaların literatüre katkı sağlayacağı düşünülmektedir. Bu şekilde, çalışmanın sonuçları, politika yapıcılara düşük maliyetli, yüksek kaliteli ve nüfusun beklentilerine duyarlı bir uzun vadeli bakım hizmetleri sistemi geliştirmelerine yardımcı olabilir. Sonuçların bu çalışmada kullanılan değişkenler açısından değerlendirilmesi gerekmekte ve farklı değişkenlerle farklı sonuçlara ulaşmanın mümkün olduğu unutulmamalıdır.