VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Analysis of Medical Imaging Devices in Türkiye Using the Malmquist Productivity Index

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ABSTRACT

Purpose: The aim of this study is to analyze the total factor productivity (TFP) of medical imaging devices in 12 regions of Türkiye for the period 2013–2022 using the Malmquist Productivity Index and to determine whether there are statistically significant differences in the TFP indicators of these devices by region and year.

Methodology: Secondary data from the Ministry of Health’s Health Statistics Yearbooks were analyzed using DEAP software with constant returns to scale (CRS) input-oriented Malmquist Productivity Index. Descriptive statistics of the data and correlations between variables were calculated with the SPSS 21.0 program, and the Mann-Whitney U test was applied to statistically test regional and temporal differences.

Findings: CT, MRI, and Doppler USG devices showed higher productivity, while ECHO and mammography exhibited lower levels. Productivity was higher in northern and western regions and lower in the south and east, with no consistent improvement observed from 2013 to 2022.

Originality: This study contributes to the literature by analyzing the TFP of medical imaging devices in 12 regions of Türkiye using the Malmquist Index, and introduces a novel approach by combining it with the Mann-Whitney U test to assess regional and temporal differences.

Keywords: Malmquist Productivity Index, Data Envelopment Analysis, Medical Imaging Devices.
JEL Codes: D24, C61, I18, L88.

Malmquist Verimlilik İndeksi ile Türkiye’deki Tıbbi Görüntüleme Cihazlarının Analizi

ÖZET

Amaç: Bu çalışmanın amacı, Malmquist Verimlilik İndeksi ile Türkiye’deki 12 bölgede 2013–2022 dönemine ait tıbbi görüntüleme cihazlarının toplam faktör verimliliğini (TFP) analiz etmek ve Türkiye’deki tıbbi görüntüleme cihazlarının toplam faktör verimlilik göstergelerinde bölgelere ve yıllara göre istatistiksel bir fark olup olmadığını belirlemektir.

Yöntem: Sağlık Bakanlığı Sağlık İstatistikleri Yıllıklarından (2013-2022) ikincil veriler, ölçeğe göre sabit getiri (CRS) girdi odaklı Malmquist Verimlilik Endeksi ile DEAP yazılımı kullanılarak analiz edilmiştir. Verilerin tanımlayıcı istatistikleri ve değişkenler arası korelasyonlar SPSS 21.0 programı ile hesaplanmış, bölgesel ve zamansal farkların istatistiksel olarak test edilmesi amacıyla Mann-Whitney U testi uygulanmıştır.

Bulgular: BT, MR ve Doppler USG cihazları daha yüksek verimlilik gösterirken, EKO ve mamografi daha düşük verimlilik göstermektedir. Verimlilik kuzey ve batı bölgelerinde daha yüksek, güney ve doğuda ise daha düşük verimlilik göstergesine sahip ve 2013'ten 2022'ye kadar istikrarlı bir iyileşme gözlemlenmemiştir.

Özgünlük: Bu çalışma, Türkiye'nin 12 bölgesinde (2013-2022) tıbbi görüntüleme cihazlarının TFP'sini Malmquist İndeksi kullanarak analiz ederek literatüre katkıda bulunmak ve bölgesel ve zamansal farklılıkları değerlendirmek için Mann-Whitney U testi ile birleştirerek yeni bir yaklaşım ortaya koymaktır.

Anahtar Kelimeler: Malmquist Verimlilik İndeksi, Veri Zarflama Analizi, Tıbbi Görüntüleme Cihazları.
JEL Kodları: D24, C61, I18, L88.

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DOI: 10.51551/verimlilik.1710968
Research Article |Submitted: 31.05.2025 |Accepted: 28.07.2025
Cite: Küçük, Y.S. (2025). “Analysis of Medical Imaging Devices in Türkiye Using the Malmquist Productivity Index”, *Verimlilik Dergisi,* 59(4), 769-786.

1. INTRODUCTION

Developed and developing countries alike face significant challenges in delivering effective healthcare services with limited resources. The goal of health policies is to maximize the positive impact on public health while ensuring cost-effectiveness (World Health Organization, 2011: 10).

With economic growth, rising healthcare expenditures and the accessibility of factors used in the production of healthcare services have become prominent issues for policymakers. Globally, there are notable inequalities in access to healthcare services and medical technologies. One potential way to reduce costs and improve equity without changing existing systems is to focus on the efficient use of medical technologies (İlgün et al., 2021)

Radiology departments, where medical technology is heavily used, play a central role in diagnosing and treating many diseases and directly affect the functioning of other clinical units. Malfunctions in these departments can delay diagnostic processes and adversely affect patient outcomes. The efficient use of high-capital radiological devices such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) is critically important for the financial performance of hospitals (Visintin et al., 2024).

Comprehensive research is needed to enable decision-makers to evaluate the efficiency of health technologies and medical devices. One of the most important resources that meet this need in Türkiye is the Health Statistics Yearbook published by the Ministry of Health. According to 2022 data, the number of MRI (11.4) and CT (15.6) devices per million people in Türkiye is below the OECD (MRI: 18.2; CT: 28.4) and EU (MRI: 17.5; CT: 26.1) averages, placing Türkiye 30th out of 41 countries. A similar trend is observed in mammography devices. However, the number of MRI (207) and CT (295) imaging procedures per 1,000 people is about twice the OECD and EU averages, placing Türkiye first among 41 countries in this metric. On the other hand, the number of physicians authorized to request examinations with medical imaging devices is 228 per 100,000 people in Türkiye, compared to 372 in OECD countries and 402 in EU countries—placing Türkiye last in this category (Republic of Türkiye Ministry of Health, 2024). Health statistics for the years 2013–2021 are largely consistent with the 2022 data. This indicates that medical imaging devices (MRI, CT, mammography) are used more intensively in Türkiye compared to OECD and EU countries. Existing studies in the literature also support this view (İlgün et al., 2021; Nak and Sağbaş, 2020; Yüksel, 2023).

Contemporary healthcare systems are increasingly struggling to meet rising service demands with limited resources. Health technologies play a critical role in this context; in particular, high-investment medical imaging devices have a direct impact on both the quality and cost of healthcare services. Although the number of medical imaging devices per one million people in Türkiye is lower than the OECD and EU country averages, the frequency of use per device is significantly higher. This indicates a notable imbalance in the healthcare system, suggesting that the limited number of devices leads to their intensive utilization in response to growing demand. However, whether this intensity translates into efficiency and effectiveness has not yet been comprehensively investigated. This gap necessitates an assessment of both the cost-effectiveness of device utilization within the healthcare system and the existence of regional disparities. In Türkiye, there is a scarcity of comprehensive analyses that measure the total factor productivity (TFP) of medical imaging devices and evaluate how this productivity has evolved over time. This study measures the productivity of medical imaging devices in 12 regions of Türkiye between 2013 and 2022 using the Malmquist Productivity Index and evaluates whether productivity differs significantly across regions and years using the Mann-Whitney U test. In the literature, there is a notable lack of long-term, region-based studies that combine the Malmquist index with statistical testing. In this respect, the study fills an empirical gap and offers an original contribution to policy-making by informing rational resource allocation, device investment planning, and efficiency-based management decisions. Based on health statistics from the past decade, the relatively intensive use of medical imaging devices in Türkiye compared to other countries forms the basis of the research question: Do the total factor productivity indicators of medical imaging devices in Türkiye differ by region and year over the past ten years?

In this context, the structure of the study is as follows: First, a literature review was conducted on efficiency analyses using the Malmquist efficiency index method in hospital services, non-communicable diseases, and primary health care. Then, the literature on data envelopment analyses performed on medical imaging devices without the Malmquist efficiency index method was reviewed. Subsequently, the methodological framework was outlined by explaining the research method, data collection tool, data analysis, and limitations. In the next section, the findings are presented in detail through analyses of secondary data obtained from the Ministry of Health's annual statistics, and the hypotheses developed in line with the research objective are tested. Finally, the findings obtained through national and international literature are discussed, and recommendations for policy and decision-makers and implications that may contribute to future studies are shared.

2. LITERATURE REVIEW

The literature review shows that the Malmquist Index and Data Envelopment Analysis (DEA) are widely used in the field of healthcare services.

Several studies have analyzed hospital efficiency using the Data Envelopment Analysis (DEA)-based Malmquist Productivity Index, with various input and output variables across different countries and time periods. For instance, in Ethiopia, Adugna et al. (2024) evaluated the efficiency of health facilities implementing performance-based financing (PBF) compared to those that did not, using three years of data (2019–2021). The output variables included the number of deliveries, antenatal care visits, fully vaccinated children, and outpatient visits, while the input variables were clinical personnel, non-clinical personnel, and allocated budget. In Norway, Lindaas et al. (2024) investigated the relationship between public and private hospital models and overall hospital performance over a nine-year period (2011–2019). Output variables included inpatient admissions through emergency services, elective inpatient care, day care treatments, and outpatient visits, while input variables were total operating costs and capital expenditures. In Serbia, Medarevic and Vukovic (2021) assessed productivity and the impact of environmental factors on hospital efficiency over five years (2015–2019). Outputs included the number of inpatients weighted by Diagnosis Related Group (DRG) coefficients and the number of outpatients, with inputs being the total number of beds, total number of non-physician healthcare staff, and total number of physicians. In China, Gong et al. (2024) analyzed the efficiency of medical and health resource allocation over a five-year period (2016–2020), using outputs such as the number of visits and hospital admissions per 10,000 population and bed utilization rate, while inputs included the number of beds, number of non-physician health workers, and number of physicians. Similarly, Li et al. (2021) measured technical efficiency over six years (2012–2017), with outputs including outpatient visits, inpatient admissions, and healthcare revenue, and inputs including total assets, active beds, and number of healthcare technical staff. Another study by Li et al. (2024) evaluated productivity dynamics over a decade (2010–2019) to inform evidence-based policy-making, using diagnostic examinations and discharged inpatients as outputs, and active beds, number of physicians, nurses, and other staff as inputs. Sun et al. (2023) analyzed how healthcare service efficiency evolved over thirteen years (2009–2021), with outputs such as number of consultations, bed occupancy rate, healthcare revenue, and mortality from infectious diseases, and inputs including number of health personnel, number of beds, and the share of health expenditure in GDP. Finally, Xu et al. (2024) conducted a 26-year analysis (1997–2022) to measure healthcare system efficiency, production technology heterogeneity, and productivity, using the number of treated patients and hospital admissions as outputs, and number of healthcare personnel, number of institutions, bed count, and public healthcare expenditures as inputs.

In the field of non-communicable diseases (NCDs), several studies have applied the DEA-Malmquist productivity model to assess the efficiency and productivity of health expenditures and systems. For instance, Arhin and Asante-Darko (2023) evaluated the efficiency and productivity of NCD-related spending in 34 Sub-Saharan African countries over a five-year period (2015–2019). The output variables included NCD-related mortality per 100,000 population, disability-adjusted life years (DALYs) due to NCDs per 100,000 population, and indicators of healthcare service coverage, financial protection, and equity in access to medical services for NCDs. Input variables comprised per capita NCD expenditure and the number of healthcare workers per 10,000 population. Similarly, Singh et al. (2021) investigated the productive efficiency of national health systems in the ASEAN region (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam) in the context of rising mortality rates from NCDs, as highlighted in the Sustainable Development Goals. This study covered a ten-year period (2007–2016), using output variables such as life expectancy at birth and NCD-related mortality rate, and input variables including per capita health expenditure, number of physicians, adult health literacy rate, per capita GDP, out-of-pocket health expenditure per capita, and the proportion of population living in rural areas.

Several studies have utilized the DEA-Malmquist productivity model to evaluate efficiency in the field of primary healthcare services. For example, Soares and Lopes (2024) assessed potential fluctuations in the total factor productivity of municipal primary healthcare services in Brazil over a five-year period (2015–2019). Output variables included the percentage of primary care coverage, vaccination coverage, primary care-related hospital admissions per 1,000 people, and the percentage of live births from mothers with at least seven antenatal visits. Input variables included the number of primary care physicians, nurses, and facilities per 100,000 population. In Greece, Trakakis et al. (2021) aimed to evaluate the primary healthcare system by analyzing data from health centers over a three-year period (2016–2018). The outputs included the number of nursing procedures, micro-surgeries, dental treatments, chronic disease cases, emergency and regular cases, referrals, transcriptions, bio-pathological and laboratory tests, as well as vaccinations for adults and for children/adolescents. Inputs consisted of the number of administrators, physicians, nursing staff, and non-medical personnel. Huang et al. (2024) conducted a nine-year (2012–2020) study in China to evaluate the efficiency of primary healthcare services and analyze their spatial distribution. Output variables were the number of visits and admissions to primary healthcare institutions, while input variables included the number of healthcare facilities, health personnel, and available beds. Zeng et al. (2024) assessed the efficiency of primary healthcare systems in China over a ten-year period (2009–2018), aiming to identify and improve the factors affecting efficiency. Outputs included the number of outpatient and inpatient visits, the proportion of outpatient and inpatient services provided at primary care institutions, and per-visit costs for both outpatient and inpatient services. Inputs comprised the number of doctors, nurses, and available beds. In another Chinese study, Zhou et al. (2023) analyzed trends in primary healthcare efficiency over eleven years (2009–2019), examining urban-rural differences and related factors. Output variables included the number of outpatient and emergency visits, and the number of discharged patients, while inputs included the number of institutions, available beds, and health technicians.

In a study conducted in 11 sample cities of Henan Province, China, Data Envelopment Analysis (DEA) was applied to evaluate the equity and efficiency of magnetic resonance imaging (MRI) services, with the aim of providing evidence-based information to support provincial-level decision-making and to optimize the configuration and utilization of MRI services. The analysis used 2017 data, with output variables including the annual number of MRI patients and annual MRI revenue, and input variables including the number of healthcare personnel, number of MRI machines, and annual operating costs (Huang et al., 2023). A study conducted in Italy applied Data Envelopment Analysis (DEA) to assess the efficiency of radiology departments in public hospitals. The analysis used 2019 data from 47 public hospitals, with output variables including the number of MRI scans, radiographic scans, and CT scans, and input variables including the number of radiologists, radiologic technologists, nurses, MRI machines, radiography machines, and CT machines (Visintin et al., 2024). In a study comparing the efficiency of medical device utilization across 81 provinces in Türkiye, Data Envelopment Analysis (DEA) was applied using output variables such as the number of imaging procedures performed with MRI, CT, ultrasound (US), Doppler US, and echocardiography (ECHO) per 1,000 outpatient visits, and input variables such as the number of MRI, CT, US, Doppler US, and ECHO devices per 100,000 population (İlgün et al., 2022). Another study compared the efficiency of medical imaging devices in Turkish hospitals for the year 2021, using DEA with output variables including the annual number of imaging procedures performed, and input variables such as the number of physicians and imaging devices (Yüksel, 2023). Unlike other studies, these four studies employed DEA to analyze data from a single year, without applying the Malmquist productivity index. Additionally, another study investigating the efficiency of the regional distribution of medical imaging devices in Türkiye used data from Nomenclature of Territorial Units for Statistics (NUTS) Level 1 regions to compare the number of medical imaging devices and imaging procedures across regions (Nak and Sağbaş, 2020).

The literature review reveals that while numerous efficiency analyses using the DEA-Malmquist model have been conducted in the fields of hospital services, non-communicable diseases (NCDs), and primary healthcare services, studies focusing on medical imaging devices (such as MRI, CT, etc.) have primarily employed input-oriented Data Envelopment Analysis (DEA) based on single-year data, rather than the Malmquist productivity approach. To date, no study—neither in Türkiye nor internationally—has been identified that evaluates the total factor productivity of medical imaging devices using the Malmquist Productivity Index. In this respect, the present study aims to fill a significant gap in the national literature. Specifically, it seeks to conduct such an analysis using data from the past decade in Türkiye.

3. METHOD

Data Envelopment Analysis (DEA) is a mathematical method commonly used to evaluate the efficiency of homogeneous Decision-Making Units (DMUs), initially developed by A. Charnes and colleagues under the assumption of constant returns to scale (CRS). It was later expanded by Banker and colleagues to incorporate variable returns to scale (VRS) (Xu et al., 2024).

Although DEA models utilize cross-sectional or time-series data, they are limited in capturing dynamic shifts in the efficiency of decision-making units (DMUs). The Malmquist Productivity Index addresses this limitation by enabling year-to-year assessments of changes in total factor productivity (TFP) through frontier analysis. Used in conjunction with DEA, the Malmquist Index facilitates both a static evaluation of efficiency in individual years and a dynamic analysis of productivity trends over time, offering a more comprehensive insight into performance changes (Zhou et al., 2023).

The Malmquist index measures the direction (increase/decrease) and magnitude of productivity change by comparing the performance of decision-making units across different time periods (Färe et al., 1994). In this respect, it is a dynamic rather than a static analytical tool. The Malmquist Productivity Index decomposes changes in total factor productivity into two main components: efficiency change and technological change. Efficiency change reflects how close a decision-making unit is to the production frontier, while technological change indicates whether the frontier itself has shifted over time, thereby capturing technological progress. This decomposition allows for a detailed understanding of whether productivity change is driven by improvements in efficiency or by technological advancements (Coelli et al., 2005). The Malmquist method is particularly suitable for systems with multiple inputs and outputs, such as healthcare services, and is widely used in such contexts (Hollingsworth, 2008).

Malmquist productivity indices are essential for tracking efficiency changes over time, relying on the assumption of a production function that accurately reflects the prevailing technological context. DEA models are instrumental in identifying the position of this production frontier (Xu et al., 2024).

$$M_0 = \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t}(x_0^{t}, y_0^{t})} * \sqrt{\frac{D_0^{t}(x_0^{t+1}, y_0^{t+1})}{D_0^{t}(x_0^{t}, y_0^{t})}} * \sqrt{\frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t}, y_0^{t})}} \qquad (1)$$

In Equation 1, x_0^t, x_0^{t+1} represent the inputs in the t region in periods t and t+1, respectively; y_0^t, y_0^{t+1} represent the outputs in the t region in periods t and t + 1, respectively (Zhou et al., 2023).

$D_0^t (x_0^t, y_0^t)$ shows the technical efficiency of the DMU for period t, while $D_0^{t+1} (x_0^{t+1}, y_0^{t+1})$ shows the technical efficiency of the DMU for period t+1. $D_0^t (x_0^{t+1}, y_0^{t+1})$ and $D_0^{t+1} (x_0^t, y_0^t)$ express the dynamic change in technical efficiency from time t to time t+1. It is calculated by replacing the data (input-output) of the DMU in period t with the data (input-output) in period t+1 (Xu et al., 2024).

In other words, $D_0^t (x_0^t, y_0^t)$ and $D_0^t (x_0^{t+1}, y_0^{t+1})$ represent the distance functions in the t period and t+1 period, respectively. If the calculated TFPCH index takes the value >1, it is thought that TFPCH increases from t to t+1 period; if it is <1, it is thought that TFPCH decreases during the same period (Zhou et al., 2023).

3.1. Data Collection Tool

The primary data source for this study is the Health Statistics Yearbook published annually by the Ministry of Health. The Decision-Making Units (DMUs) in the analysis were defined as 12 regional groups based on The Nomenclature of Territorial Units for Statistics (NUTS) Level 1 classification: West Marmara, Istanbul, East Marmara, Aegean, Mediterranean, West Anatolia, Central Anatolia, West Black Sea, East Black Sea, Northeast Anatolia, Central East Anatolia, and Southeast Anatolia. The main objective of this study is to analyze the total factor productivity (TFP) of medical imaging devices in these 12 regions of Türkiye between 2013 and 2022 using the Malmquist Productivity Index, and to determine whether there are statistically significant differences in TFP indicators by region and year. The research hypotheses developed in line with the study's objective are as follows:

H1.1: There is a statistically significant difference in the average total factor productivity of medical imaging devices between high-productivity and low-productivity regions in Türkiye.

H1.2: There is a statistically significant difference in the average total factor productivity of medical imaging devices between high-productivity and low-productivity years in Türkiye.

To test the developed research hypotheses, this study utilized secondary data. The secondary data obtained from the Annual Statistics of the Ministry of Health include a wide range of parameters, such as the number of medical imaging devices (MRI, CT, mammography, ultrasonography, Doppler, and echocardiography), the number of procedures performed by these devices, and the total number of physicians, dentists, and nurses. In this study, the selection of appropriate input and output variables is of critical importance for the analysis of the efficiency of medical imaging devices.

A review of the existing literature shows that input variables in such analyses typically include the number of relevant medical imaging devices and the number of healthcare professionals operating these devices (e.g., physicians, radiologists, and technicians), while the output variable is generally the total number of imaging procedures performed. This approach provides a meaningful foundation for quantitatively representing healthcare service production processes and enables the measurement of efficiency levels based on output per unit (Huang et al., 2023; İlgün et al., 2022; Visintin et al., 2024; Yüksel, 2023).

Based on this information from the literature, for the DEA-Malmquist productivity index analysis, the output variable was defined as the number of imaging procedures per 1,000 outpatient visits, while the input variables were defined as the number of physicians per 100,000 population and the number of medical imaging devices per 1,000,000 population. However, it is considered necessary that there be a statistically significant relationship—at the 5% significance level within a 95% confidence interval—between the input and output variables used in the Malmquist productivity index, which is a non-parametric analysis. The Spearman's rho correlation coefficients, which assess the correlation between non-parametric variables, are presented in Table 1.

Table 1. Spearman's Rho correlation coefficients between variables

Device Type	*Significant Correlation Between Device Count and Imaging Volume*	*Significant Correlation Between Physician Count and Imaging Volume*
MRI	r=0.498*	r=0.615*
CT	r=0.283*	r=0.464*
USG	r=-0.092	r=-0.466*
Doppler USG	r=0.675*	r=0.448*
ECHO	r=0.474*	r=0.381*
Mammography	r=0.756*	r=0.611*

Note: * means correlation is significant at the 0.01 level

The SPSS 21.0 package program used in the study calculated the relationship coefficients between the variables. When Table 1 was examined, it was seen that there was no statistically significant relationship only between the number of ultrasound (USG) devices per 1,000,000 people and the number of ultrasound (USG) imaging requested for every 1,000 examinations (p:0.319). It was seen that there was a statistically significant relationship between the other variables at a significance level of 1% and a confidence interval of 99% ($p \leq 0.002$). While the variables with a statistically significant relationship between the variables were used within the scope of inputs and outputs in the Malmquist efficiency index, the variables with no statistically significant relationship between the variables were excluded from the relevant analysis. Therefore, the inputs and outputs to be used in the Malmquist efficiency index are shown in Table 2.

Table 2. Inputs and outputs for the Malmquist Productivity Index – DEA model

Device	*Input*	*Output*
MRI	MRI devices, Physicians	MRI scans
CT	CT devices, Physicians	CT scans
Doppler USG	Doppler USG devices, Physicians	Doppler USG scans
ECHO	ECHO devices, Physicians	ECHO scans
Mammography	Mammography devices, Physicians	Mammography scans

3.2. Data Analysis

The Malmquist Productivity Index evaluates changes in technical efficiency by calculating technological progress and productivity change over time. The model shows the dynamic trend in total factor productivity change (TFPCH) by comparing outputs across different time periods for Decision-Making Units (DMUs). In Equation 2, technical efficiency (EFFCH) itself consists of pure technical efficiency (PECH) and scale efficiency (SECH). In Equation 3, the TFPCH in this model is composed of technical efficiency change (EFFCH) and technological change (TECHCH) (Gong et al., 2024; Zhou et al., 2023). The relationships among the components are as follows:

$$EFFCH = PECH \times SECH \tag{2}$$

$$TFPCH = EFFCH \times TECHCH \tag{3}$$

If any of these productivity changes are greater than 1, this indicates positive growth or improvement. A value equal to 1 indicates stagnation or no change, while a value less than 1 shows decline or deterioration in productivity.

DEA was first introduced by Charnes et al., (1978) influenced by Farrell (1957), under the assumption of constant returns to scale (CRS) (Charnes et al., 1978; Farrell, 1957). In this model, it is assumed that if a DMU increases its inputs proportionally, the increase in outputs will be at the same rate. Later, Banker et al. developed the variable returns to scale (VRS) model, which allows for output increases to be either more or less than the input increases, thus capturing increasing or decreasing returns to scale (Banker et al., 1984). The CRS model reflects total efficiency resulting from both scale efficiency and pure technical efficiency due to administrative performance. On the other hand, the VRS model represents only pure technical efficiency, excluding the scale component. The productivity scores obtained in DEA depend on whether the CRS or VRS model is adopted. Another factor influencing DEA productivity scores is whether the analysis is input-oriented or output-oriented. In other words, the criteria for DEA to be considered efficient or inefficient include whether it is input-oriented or output-oriented. If a DMU can increase its outputs without increasing any inputs, it is considered output-oriented. If a DMU can reduce its inputs without reducing any outputs, it is considered input-oriented (Charnes et al., 1981).

For this study, the input-oriented CRS model was selected. The choice of an input-oriented approach is based on the fact that most DEA studies in healthcare use input-oriented models, since management in healthcare generally has more control over inputs than outputs (Chern and Wan, 2000; İlgün et al., 2022;

Ozcan, 2008). The CRS model was preferred because it allows for comparing regions (based on NUTS Level 1) not only in terms of size but also in terms of pure technical efficiency due to managerial performance.

Microsoft Office, SPSS 21.0, and DEAP 2.1 software were used for data entry and analysis. The number of medical imaging devices, the number of scans performed by these devices, and the total number of physicians in Türkiye from 2013 to 2022 (as published in the Health Statistics Yearbooks) were compiled in Microsoft Excel. Then, the input-oriented CRS model in the DEAP software was used to calculate the total factor productivity of medical imaging devices using the Malmquist Productivity Index. Descriptive findings and correlation coefficients between variables were calculated using SPSS 21.0. The Mann-Whitney U test was used to determine whether there were statistically significant differences in the average TFP values of medical imaging devices across different regions and years in Türkiye.

3.3. Limitations

The Malmquist Productivity Index method used in this study is a powerful tool for analyzing changes in productivity over time; however, it has certain limitations. One of the primary constraints is its inability to distinguish the source of technological progress. In other words, it cannot determine whether the observed technological change coefficient stems from internal innovation or external factors. This may introduce ambiguity in the interpretation of the results.

Furthermore, the data used in this study were entirely derived from secondary sources. The data were obtained from publicly available official statistics (Ministry of Health), and their accuracy and completeness could not be independently verified by the researcher. This may introduce implicit measurement errors in the outputs analyzed (e.g., number of imaging procedures) and the input variables (e.g., number of devices, number of healthcare personnel).

The study relied solely on quantitative outputs (e.g., total number of imaging procedures). However, using only volume-based outputs in efficiency analyses may not adequately reflect service quality. Indicators related to quality—such as the effectiveness of device usage, diagnostic accuracy, or repeat scan rates—were excluded from the analysis. As such, the findings reflect only the productivity dimension and do not encompass clinical effectiveness or patient outcomes.

In addition, there are notable disparities among regions in Türkiye regarding healthcare infrastructure, distribution of specialist personnel, and access to services. Structural inequalities observed between metropolitan and rural areas may result in some regions having a relative advantage. These external disparities could introduce bias into regional comparisons within the model.

The impact of the COVID-19 pandemic on the delivery of healthcare services is briefly addressed in the findings section. Data from the pandemic period may deviate from typical productivity trends. Although this effect is briefly acknowledged, its influence on the analysis has not been examined in detail, which may limit the temporal validity of the results.

Finally, the input and output variables used in the study were selected in accordance with established practices in the literature. Despite this, all of the aforementioned limitations suggest that the findings should be interpreted within specific contextual boundaries. Caution should be exercised when generalizing the results, and these constraints should be carefully considered in their interpretation.

4. RESULTS

Descriptive findings related to medical imaging devices and the total number of physicians for 12 regions (as defined by NUTS-1) from 2013 to 2022, as published in the Ministry of Health's Health Statistics Yearbooks, are presented in Table 3.

Table 3. Descriptive statistics for medical imaging devices

Variables	*n*	*Mean*	*SD*	*Min*	*Max*
MRI devices	120	10.41	1.51	7.50	13.80
MRI scans	120	30.20	5.20	20.70	46.50
CT devices	120	14.54	1.87	11.00	18.20
CT scans	120	40.78	12.99	20.50	77.90
Doppler USG devices	120	61.44	19.77	27.20	126.40
Doppler USG scans	120	32.44	10.19	10.90	60.20
ECHO devices	120	28.13	6.28	13.60	46.50
ECHO scans	120	17.23	1.95	12.30	21.60
Mammography devices	120	11.12	2.09	6.90	14.90
Mammography scans	120	4.23	1.62	1.20	7.40
Total number of physicians	120	184.14	41.39	121.00	346.00

As shown in Table 3, when examining the average number of devices per 1,000,000 population, Doppler ultrasound devices were found to be the most prevalent, while MRI machines were the least common. This finding is thought to be related to the cost differences among the devices. Similarly, when evaluating the average number of imaging procedures requested per 1,000 outpatient visits, CT scans had the highest frequency, whereas mammography had the lowest. The relatively low number of mammography procedures—despite their critical role in the early detection of breast cancer in women—highlights an important issue for policymakers in the context of preventive healthcare services.

Table 4. Malmquist Productivity Index indicators for MRI devices by region and year (2013–2022)

Region / Year	*pech*	*sech*	*Effch*	*techch*	*tfpch*
West Marmara	1.005	1.000	1.005	1.035	1.040
Istanbul	0.991	0.990	0.981	1.040	1.021
East Marmara	1.013	0.992	1.005	1.033	1.039
Aegean	1.025	0.977	1.001	1.034	1.035
Mediterranean	1.006	0.987	0.993	1.034	1.027
West Anatolia	1.006	0.993	0.999	1.025	1.024
Central Anatolia	1.018	0.995	1.013	1.035	1.048
West Black Sea	1.016	0.974	0.990	1.035	1.025
East Black Sea	0.997	0.984	0.982	1.040	1.021
Northeast Anatolia	1.000	1.000	1.000	1.035	1.035
Central East Anatolia	0.990	0.979	0.969	1.027	0.996
Southeast Anatolia	1.000	0.966	0.966	1.035	1.000
Average	1.006	0.986	0.992	1.034	1.026
Türkiye 2013-2014	1.006	0.975	0.981	1.094	1.073
Türkiye 2014-2015	1.037	0.947	0.982	1.038	1.019
Türkiye 2015-2016	1.003	1.075	1.079	0.937	1.011
Türkiye 2016-2017	1.029	1.001	1.031	1.012	1.043
Türkiye 2017-2018	1.007	1.041	1.048	0.975	1.022
Türkiye 2018-2019	1.046	0.997	1.043	0.985	1.027
Türkiye 2019-2020	0.991	0.982	0.973	1.094	1.065
Türkiye 2020-2021	0.960	0.986	0.946	1.087	1.029
Türkiye 2021-2022	0.975	0.884	0.862	1.099	0.947

Table 4 presents the average MR device values and annual Malmquist index changes for 12 NUTS regions in Türkiye from 2013 to 2022. According to Table 4; across Türkiye between 2013 and 2022, the average technical efficiency (EFFCH) for MRI devices—comprised of pure efficiency (PECH) and scale efficiency (SECH)—was 0.992, indicating 0.8% inefficiency. When technical efficiency is considered alongside technological change (TECHCH), the region with the lowest total factor productivity (TFPCH) is Central East Anatolia (0.996), indicating a 0.4% productivity loss. The region with the highest TFPCH is Central Anatolia (1.048), reflecting a 4.8% productivity increase. Although the Eastern Anatolia region exhibited a high level of technological progress (techch: 1.027), the overall change in total factor productivity remained low, which can be attributed to a decrease in technical efficiency (effch: 0.969). This may be explained by the fact that physicians in this region request fewer MRI scans compared to those in other regions, or that the number of physicians per 100,000 population is lower in this region than in others. The year with the lowest productivity is 2022 compared to 2021 (TFPCH: 0.947), while the year with the highest productivity is 2014 compared to 2013 (TFPCH: 1.073). The decrease in physicians' MRI scan requests in 2022 compared to the previous year can be attributed to the post-COVID-19 normalization process, which led to a reduction in MRI diagnostic requests. On average, the 12 regions had a 2.6% increase in productivity (mean TFPCH: 1.026). Only one region and one year had a TFPCH value below 1, indicating a decline, while the others had stable or improved productivity.

Table 5 presents the average CT device values for the 12 NUTS regions from 2013 to 2022, along with Türkiye's annual Malmquist productivity changes. According to Table 5; between 2013 and 2022, the technical efficiency (effch) of CT devices in Türkiye—comprising pure efficiency (pech) and scale efficiency (sech)—increased annually by an average of 2.1% (1.021). When combined with technological change (techch), total factor productivity (tfpch) was lowest in Southeastern Anatolia (0.999) and highest in the Aegean Region (1.076). Although the Southeastern Anatolia region exhibited a high level of technological progress (techch: 1.013), the low change in total factor productivity can be attributed to a decrease in technical efficiency (effch: 0.987). This may be explained by physicians in this region requesting fewer CT scans compared to those in other regions, or by a lower number of physicians per 100,000 population in this region relative to others. At the yearly level, the sharpest decline occurred in 2022 (0.817), while the most significant increase was in 2020 (1.720). The excessive use of CT scans—considered the gold standard test for diagnosing COVID-19—in 2020, the year the pandemic began, can explain the high efficiency level of 72% observed for CT devices in that year. The decrease in physicians' CT scan requests in 2022 compared to the previous year can be attributed to the post-COVID-19 normalization process, which led to a reduction in CT diagnostic requests. On average, the tfpch across the 12 NUTS regions was 1.044. While 11 regions and 7 years recorded productivity scores of 1 or above, one region and two years fell below this threshold.

Table 5. Malmquist Productivity Index indicators for CT devices by region and year (2013–2022)

Region / Year	*pech*	*sech*	*Effch*	*techch*	*tfpch*
West Marmara	1.011	1.046	1.058	1.011	1.070
Istanbul	0.985	1.023	1.007	1.034	1.041
East Marmara	1.000	1.019	1.019	1.033	1.053
Aegean	1.031	1.009	1.040	1.035	1.076
Mediterranean	1.014	1.010	1.025	1.012	1.037
West Anatolia	1.008	1.014	1.022	1.035	1.058
Central Anatolia	1.003	1.022	1.025	1.032	1.058
West Black Sea	1.022	1.012	1.035	1.022	1.058
East Black Sea	1.017	1.012	1.028	1.024	1.053
Northeast Anatolia	0.995	1.006	1.001	1.011	1.012
Central East Anatolia	1.001	1.000	1.001	1.018	1.018
Southeast Anatolia	1.000	0.987	0.987	1.013	0.999
Average	1.007	1.013	1.021	1.023	1.044
Türkiye 2013-2014	1.008	1.016	1.025	1.073	1.100
Türkiye 2014-2015	1.026	1.065	1.093	0.938	1.025
Türkiye 2015-2016	0.998	1.019	1.017	0.994	1.011
Türkiye 2016-2017	1.027	1.029	1.056	0.992	1.048
Türkiye 2017-2018	0.990	0.985	0.976	1.061	1.035
Türkiye 2018-2019	1.014	1.015	1.030	0.974	1.003
Türkiye 2019-2020	0.965	1.018	0.982	1.752	1.720
Türkiye 2020-2021	1.017	0.940	0.956	0.887	0.848
Türkiye 2021-2022	1.022	1.036	1.059	0.771	0.817

Table 6. Malmquist Productivity Index Indicators for Doppler USG devices by region and year (2013–2022)

Region / Year	*pech*	*sech*	*effch*	*techch*	*tfpch*
West Marmara	1.019	1.066	1.086	0.981	1.066
Istanbul	1.038	0.985	1.022	0.996	1.019
East Marmara	1.009	0.998	1.007	0.974	0.981
Aegean	1.016	1.029	1.045	0.954	0.996
Mediterranean	1.007	1.016	1.023	0.976	0.998
West Anatolia	1.059	1.012	1.071	0.964	1.032
Central Anatolia	0.993	1.068	1.061	1.011	1.072
West Black Sea	0.986	1.017	1.003	0.968	0.971
East Black Sea	1.014	1.047	1.062	0.991	1.052
Northeast Anatolia	0.979	1.031	1.010	0.999	1.009
Central East Anatolia	1.000	0.997	0.997	0.978	0.975
Southeast Anatolia	1.000	1.002	1.002	0.980	0.982
Average	1.010	1.022	1.032	0.981	1.012
Türkiye 2013-2014	0.976	1.087	1.061	0.976	1.036
Türkiye 2014-2015	1.033	1.009	1.042	0.926	0.965
Türkiye 2015-2016	0.964	1.054	1.016	1.073	1.090
Türkiye 2016-2017	0.999	1.030	1.029	1.095	1.127
Türkiye 2017-2018	1.029	0.999	1.028	0.937	0.964
Türkiye 2018-2019	1.093	1.039	1.136	1.033	1.174
Türkiye 2019-2020	0.908	0.946	0.859	1.132	0.973
Türkiye 2020-2021	1.063	0.999	1.063	0.842	0.895
Türkiye 2021-2022	1.033	1.042	1.076	0.857	0.923

Table 6 presents the average doppler ultrasound (USG) device values for the 12 NUTS regions from 2013 to 2022, along with Türkiye's annual Malmquist productivity changes. According to Table 6; between 2013 and 2022, the technical efficiency (effch) of doppler USG devices in Türkiye, derived from pure efficiency (pech) and scale efficiency (sech), showed an average annual improvement of 3.2% (1.032). When combined with technological change (techch), the lowest total factor productivity (tfpch) was observed in the Western Black Sea Region (0.971), while the highest was in Central Anatolia (1.072). Although the Western Black Sea region exhibited a high level of technical efficiency (effch: 1.003), the low change in total factor productivity can be attributed to a decline in technological progress (techch: 0.968). This may be explained by the Doppler ultrasonography devices in this region being of lower technological quality compared to those in other regions, or by the number of Doppler ultrasonography devices per 1,000,000 population being lower than in other regions. The sharpest annual decline occurred in 2021 compared to 2020 (0.895), and the greatest increase was recorded in 2019 relative to 2018 (1.174). The decrease in physicians' Doppler ultrasonography (USG) requests in 2021 compared to the previous year can be attributed to the postponement of elective procedures during the COVID-19 pandemic, as healthcare services primarily focused on the diagnosis and treatment of coronavirus cases, leading to a decline in Doppler USG diagnostic requests. On average, the tfpch index across the 12 NUTS regions was 1.012, indicating a 1.2% productivity gain. Six regions and five years recorded tfpch values below 1, whereas the remaining six regions and four years achieved scores equal to or above 1.

Table 7. Malmquist Productivity Index indicators for ECHO devices by region and year (2013–2022)

Region / Year	*pech*	*sech*	*effch*	*techch*	*tfpch*
West Marmara	0.996	1.004	1.000	0.973	0.973
Istanbul	0.987	1.013	1.000	0.977	0.977
East Marmara	0.996	1.013	1.010	0.984	0.993
Aegean	1.033	0.978	1.011	0.953	0.963
Mediterranean	1.000	0.996	0.996	0.974	0.971
West Anatolia	0.987	1.035	1.021	0.953	0.973
Central Anatolia	1.011	1.001	1.012	0.975	0.986
West Black Sea	1.012	0.988	1.000	0.980	0.980
East Black Sea	1.008	1.000	1.008	0.992	1.000
Northeast Anatolia	0.977	0.992	0.969	0.973	0.943
Central East Anatolia	0.986	1.000	0.986	0.970	0.957
Southeast Anatolia	1.000	1.000	1.000	0.973	0.973
Average	0.999	1.001	1.001	0.973	0.974
Türkiye 2013-2014	1.003	0.984	0.987	1.051	1.037
Türkiye 2014-2015	1.046	1.046	1.094	0.892	0.976
Türkiye 2015-2016	0.971	1.009	0.980	0.974	0.954
Türkiye 2016-2017	0.949	1.011	0.960	1.072	1.029
Türkiye 2017-2018	1.017	1.018	1.034	0.954	0.987
Türkiye 2018-2019	1.071	0.990	1.061	0.926	0.982
Türkiye 2019-2020	1.028	0.995	1.023	0.875	0.895
Türkiye 2020-2021	0.970	0.989	0.959	1.039	0.996
Türkiye 2021-2022	0.948	0.974	0.923	0.994	0.917

Table 7 presents the average echocardiography (ECHO) device values for the 12 NUTS regions from 2013 to 2022, along with Türkiye's annual Malmquist productivity changes. According to Table 7; from 2013 to 2022, the technical efficiency (effch) of ECHO devices in Türkiye, comprising pure technical efficiency (pech) and scale efficiency (sech), increased marginally by 0.1% (1.001) on average. When combined with technological change (techch), total factor productivity (tfpch) was lowest in Northeastern Anatolia (0.943) and highest in the Eastern Black Sea Region (1.000), indicating stable productivity. Considering that all 12 regions in the NUTS (Nomenclature of Territorial Units for Statistics) classification exhibited low levels of technological progress (techch < 1.000), the low total factor productivity change observed in the Northeastern Anatolia region can be attributed to a decline in technical efficiency (effch: 0.969). This may be explained by the lower number of echocardiography (ECHO) requests made by physicians in this region compared to those in other regions, or by the lower number of physicians per 100,000 population in this region relative to others. The sharpest annual decline occurred in 2020 compared to 2019 (0.895), while the highest increase was in 2014 relative to 2013 (1.037). The decrease in physicians' echocardiography (ECHO) requests in 2020 compared to the previous year can be attributed to the postponement of elective procedures during the COVID-19 pandemic, as healthcare services focused primarily on the diagnosis and treatment of coronavirus cases, leading to a reduction in ECHO diagnostic requests. On average, the tfpch across 12 NUTS regions indicated a 2.6% decline (0.974). Among the regions, 11 recorded tfpch values below 1, and only one showed no change (1.000). Similarly, 7 of the 9 years observed had tfpch values below 1, while only 2 years showed productivity stability or growth.

Table 8 presents the average mammography device values for the 12 NUTS regions from 2013 to 2022, along with Türkiye's annual Malmquist productivity changes. According to Table 8; between 2013 and 2022, the technical efficiency (effch) of mammography devices in Türkiye—comprising pure efficiency (pech) and scale efficiency (sech)—remained stable at 1.000. When combined with technological change (techch), total factor productivity (tfpch) was lowest in the Mediterranean Region (0.943) and highest in Western Anatolia (0.999), though still below the baseline. Considering that all 12 regions exhibited low levels of technological progress (techch < 1.000), the low total factor productivity change in the Mediterranean region can be attributed to a decline in technical efficiency (effch: 0.982). This may be due to the mammography devices in this region being of lower technological quality compared to those in other regions, or to a lower number of mammography devices per 1,000,000 population in the region. The greatest decline occurred in 2015 compared to 2014 (0.717), while the highest improvement was observed in 2021 relative to 2020 (1.192). All 12 NUTS regions recorded tfpch values below 1, indicating a general decline. Across the 9-year period, 5 years showed values below 1, and 4 years had tfpch values equal to or above 1. On average, total factor productivity declined by 3.3% (0.967) across all regions.

Table 8. Malmquist Productivity Index indicators for mammography devices by region and year (2013–2022)

Region / Year	*pech*	*sech*	*effch*	*techch*	*tfpch*
West Marmara	0.998	1.005	1.003	0.961	0.964
Istanbul	1.000	1.001	1.001	0.971	0.972
East Marmara	1.000	1.000	1.000	0.966	0.966
Aegean	1.000	1.009	1.009	0.967	0.976
Mediterranean	0.993	0.988	0.982	0.960	0.943
West Anatolia	1.000	1.017	1.017	0.982	0.999
Central Anatolia	0.993	0.971	0.964	0.979	0.944
West Black Sea	1.005	1.014	1.018	0.960	0.977
East Black Sea	0.999	1.010	1.009	0.957	0.966
Northeast Anatolia	1.000	0.970	0.970	0.977	0.948
Central East Anatolia	1.005	1.023	1.028	0.970	0.997
Southeast Anatolia	1.000	0.998	0.998	0.961	0.959
Average	0.999	1.000	1.000	0.968	0.967
Türkiye 2013-2014	0.963	0.956	0.920	1.140	1.049
Türkiye 2014-2015	1.048	1.069	1.121	0.729	0.817
Türkiye 2015-2016	0.975	0.984	0.960	0.933	0.895
Türkiye 2016-2017	0.972	0.912	0.887	1.092	0.968
Türkiye 2017-2018	1.009	0.990	0.999	0.958	0.956
Türkiye 2018-2019	1.019	0.992	1.011	0.991	1.002
Türkiye 2019-2020	1.010	1.104	1.116	0.751	0.838
Türkiye 2020-2021	0.990	0.942	0.933	1.279	1.192
Türkiye 2021-2022	1.011	1.071	1.082	0.964	1.043

Table 9. Total Factor Productivity (tfpch) indicators of medical imaging devices by region and year

Region / Year	*CT*	*MR*	*Doppler USG*	*ECHO*	*Mammography*	*Avr.*
West Marmara	1.070	1.040	1.066	0.973	0.964	1.023
Central Anatolia	1.058	1.048	1.072	0.986	0.944	1.022
East Black Sea	1.053	1.021	1.052	1.000	0.966	1.018
West Anatolia	1.058	1.024	1.032	0.973	0.999	1.017
Aegean	1.076	1.035	0.996	0.963	0.976	1.009
Istanbul	1.041	1.021	1.019	0.977	0.972	1.006
East Marmara	1.053	1.039	0.981	0.993	0.966	1.006
East Black Sea	1.058	1.025	0.971	0.980	0.977	1.002
Mediterranean	1.037	1.027	0.998	0.971	0.943	0.995
Northeast Anatolia	1.012	1.035	1.009	0.943	0.948	0.989
Central East Anatolia	1.018	0.996	0.975	0.957	0.997	0.989
Southeast Anatolia	0.999	1.000	0.982	0.973	0.959	0.983
Average	1.044	1.026	1.012	0.974	0.967	1.005
Türkiye 2019-2020	1.720	1.065	0.973	0.895	0.838	1.098
Türkiye 2013-2014	1.100	1.073	1.036	1.037	1.049	1.059
Türkiye 2016-2017	1.048	1.043	1.127	1.029	0.968	1.043
Türkiye 2018-2019	1.003	1.027	1.174	0.982	1.002	1.038
Türkiye 2017-2018	1.035	1.022	0.964	0.987	0.956	0.993
Türkiye 2015-2016	1.011	1.011	1.090	0.954	0.895	0.992
Türkiye 2020-2021	0.848	1.029	0.895	0.996	1.192	0.992
Türkiye 2014-2015	1.025	1.019	0.965	0.976	0.817	0.960
Türkiye 2021-2022	0.817	0.947	0.923	0.917	1.043	0.929

Table 9 presents the total factor productivity (tfpch) indicators based on the average values for 12 NUTS regions and annual changes for Türkiye between 2013 and 2022. According to Table 9; Between 2013 and 2022, the average annual total factor productivity (tfpch) values of medical imaging devices across Türkiye and its NUTS regions, ranked from highest to lowest, were as follows: CT (4.4% productivity gain; 1.044), MRI (2.6% gain; 1.026), Doppler USG (1.2% gain; 1.012), ECHO (2.6% productivity decline; 0.974), and mammography (3.3% decline; 0.967). The 3.3% productivity decline observed in mammography devices—critical for early detection of breast cancer in women—along with the 2.6% decline in ECHO devices—vital for diagnosing and monitoring heart conditions and early detection of heart attacks—warrants the attention of policymakers and decision-makers.

Due to the insufficient sample size (n<30) to test the research hypotheses, the non-parametric Mann-Whitney U test was employed to compare regions and years based on the total factor productivity (tfpch) averages of medical imaging devices categorized as low (tfpch<1) and high (tfpch>1).

Table 10. Findings on the comparative analysis of total factor productivity of medical imaging devices in Türkiye's nuts regions

12 NUTS regions in Türkiye		*n*	*Mean Rank*	*Sum of Ranks*	*Z*	*p*
MRI device	Low**	1	1.0	1.0	-1.599	0.110
	High***	11	7.0	77.0		
CT device	Low**	1	1.0	1.0	-1.607	0.108
	High***	11	7.0	77.0		
Doppler USG device	Low**	6	3.5	21.0	-2.882	0.004*
	High***	6	9.5	57.0		
ECHO device	Low**	11	6.0	66.0	-1.605	0.109
	High***	1	12.0	12.0		
Mammography device	Low**	12	6.5	78.0	null	null
	High***	0	0.0	0.0		
The average of medical imaging devices	Low**	4	2.5	10	-2.717	0.007*
	High***	8	8,5	68		

Note: *, p<0.05; **, tfpch<1; ***, tfpch>1

According to Table 10, no comparison could be made for mammography devices, as their total factor productivity (tfpch) values were below 1 in all 12 NUTS regions. For MRI, CT, and ECHO devices, no statistically significant difference was found between regions with high and low tfpch values (p>0.05). In contrast, a statistically significant difference was observed for Doppler USG devices based on tfpch performance (p=0.004). Similarly, a significant difference was found in the average total factor productivity of medical imaging devices across the 12 regions depending on whether tfpch was below or above 1 (p=0.007). Thus, the research hypothesis (H1.1) was accepted. According to Table 9, the regions with average tfpch values above 1 for medical imaging devices were West Marmara, Central Anatolia, Eastern Black Sea, West Anatolia, Aegean, Istanbul, East Marmara, and West Black Sea. On the other hand, the Mediterranean, Northeastern Anatolia, Central Eastern Anatolia, and Southeastern Anatolia regions showed average tfpch values below 1. The consistently low productivity levels (tfpch<1) of medical imaging devices in Türkiye's southern and eastern regions warrant the attention of professional healthcare managers.

Table 11. Comparative findings on the total factor productivity of medical imaging devices in Türkiye (2014–2022)

The period 2014–2022 in Türkiye		*n*	*Mean Rank*	*Sum of Ranks*	*Z*	*p*
MRI device	Low**	1	1.0	1,0	-1,549	0,121
	High***	8	5.5	44,0		
CT device	Low**	2	1.5	3,0	-2,049	0,040*
	High***	7	6.0	42,0		
Doppler USG device	Low**	5	3.0	15,0	-2,449	0,014*
	High***	4	7.5	30,0		
ECHO device	Low**	7	4.0	28,0	-2,049	0,040*
	High***	2	8.5	17,0		
Mammography device	Low**	5	3.0	15,0	-2,449	0,014*
	High***	4	7.5	30,0		
The average of medical imaging devices	Low**	5	3.0	15	-2,449	0,014*
	High***	4	7.5	30		

Note: *, p<0.05; **, tfpch<1; ***, tfpch>1

According to Table 11, no statistically significant difference was found in the total factor productivity (TFP) of MRI devices in Türkiye between years with high and low productivity levels from 2014 to 2022 ($p>0.05$). In contrast, statistically significant differences were observed for CT, Doppler USG, ECHO, and mammography devices based on whether their TFP values were above or below 1 ($p<0.05$). A significant difference was also found between years with high and low average TFP values of all medical imaging devices in Türkiye ($p = 0.014$). Therefore, the research hypothesis (H1.2) was accepted. Based on Table 9, the years in which the average TFP of medical imaging devices exceeded 1 were 2014, 2017, 2019, and 2020, whereas 2015, 2016, 2018, 2021, and 2022 were characterized by TFP values below 1. The fluctuation in productivity—initially high, followed by a period of decline—suggests a lack of consistent performance, which merits the attention of policymakers and decision-makers. Notably, in 2020, the onset of the COVID-19 pandemic, the CT device was widely used as the gold standard diagnostic tool, which likely contributed to the spike in TFP. However, the decline in productivity observed in the subsequent two years (2021 and 2022) indicates a concerning trend in the post-pandemic period that should be addressed by healthcare authorities.

5. DISCUSSION

The literature review was conducted within the scope of monitoring the regional and temporal variations in the efficiency levels of national healthcare systems, in line with the research question addressed in this study.

In a study conducted in Ethiopia covering the years 2019–2021, health facilities implementing performance-based financing (PBF) were found to have lower Total Factor Productivity (TFP) indices compared to those that did not implement PBF (Adugna et al., 2024). The annual TFP indices for each health facility reported in the study by Adugna et al. (2024) showed a decline in TFP in the second year, followed by an increase in the third year. This pattern is similar to the findings of the present study, which observed initially low and subsequently higher productivity indicators in the TFP indices of medical imaging devices throughout the 2013–2022 period.

A study conducted in Norway identified a relationship between various factors—such as realized budgets, staffing levels, and hospital structure—and efficiency (Lindaas et al., 2024). In the study by Lindaas et al. (2024), the performance of hospitals between 2011 and 2019 was evaluated using the Malmquist Productivity Index, revealing an average annual increase of 0.27%. Similarly, in the present study, the average annual increase in the TFP indices of medical imaging devices across all healthcare institutions in Türkiye between 2013 and 2022 was found to be 0.5% across 12 regions. Both studies exhibit a comparable trend in that the TFP indices remained above 1 over a ten-year period, indicating increasing productivity.

In a study conducted on Serbian hospitals, 28 out of 39 hospitals showed improvement in Total Factor Productivity (TFP) between 2015 and 2019 (Medarevic and Vukovic, 2021). The study by Medarevic and Vukovic (2021) found that the number of hospitals with a Malmquist index above 1 was highest in the pre-pandemic year 2018–2019. This is similar to the findings of the present study, in which the average Total Factor Productivity of medical imaging devices in the pre-pandemic year 2018–2019 was also above 1 (1.038).

In a study conducted across 34 Sub-Saharan African countries between 2015 and 2019, the efficiency of healthcare services for non-communicable diseases was found to have declined by an average of 3.2% (tfpch: 0.968) over the period (Arhin and Asante-Darko, 2023). The study by Arhin and Asante-Darko (2023) also revealed that Total Factor Productivity Change (tfpch) recorded growth only in 2018, with the performance of all components fluctuating inconsistently over the years. This pattern aligns with the findings of the present study, which similarly observed inconsistent changes in productivity over time.

A study conducted in Brazil revealed a decline in Total Factor Productivity (TFP) in the primary healthcare sector between 2015 and 2019 (Soares and Lopes, 2024). In the study by Soares and Lopes (2024), 75% of Brazilian municipalities experienced stagnation or a decrease in TFP in primary healthcare services. In contrast, the present study found that only 33% of the 12 regions in Türkiye experienced stagnation or a decline in the TFP of medical imaging devices over a ten-year period, indicating a dissimilar pattern.

In a study evaluating the period between 2016 and 2018 in Greece, the Total Factor Productivity (TFP) of all 155 primary healthcare centers was estimated using an input-oriented Malmquist Productivity Index under Data Envelopment Analysis (DEA). Subsequently, Spearman's rank correlation coefficients were calculated for four different models constructed with varying inputs and outputs. The Spearman's rank correlation tests demonstrated statistically significant correlations among the different model specifications, supporting internal validity (Trakakis et al., 2021). In the present study, the Mann–Whitney U test, a non-parametric method, was used to assess whether there were statistically significant differences in TFP indices across 12 regions and over the years 2013–2022. Both studies are similar in that they employed statistical methods to examine whether there were relationships or differences in TFP indices, thus showing a methodological resemblance.

A study conducted in China's Hainan Province found that the allocation efficiency of medical and health resources was generally low and exhibited a declining trend from 2016 to 2020 (Gong et al., 2024). Furthermore, the study by Gong et al. (2024) reported that although economically developed areas with large populations in Hainan were relatively more efficient than other regions, there were significant regional disparities. This finding aligns with the results of the present study, which also confirmed the hypothesis that regional differences exist in Total Factor Productivity.

A study conducted on healthcare institutions in China found that the regional allocation of efficiency was unbalanced and that there were significant differences in the scale of healthcare institutions across the country between 2012 and 2017 (Li et al., 2021), which is consistent with the findings of the present study.

In a study analyzing regional healthcare service delivery across 31 provinces in China from 2010 to 2019, it was shown that following the implementation of the new healthcare reform in 2009, regional health inputs and outputs in all provinces exhibited varying degrees of growth (Li et al., 2024). The study by Li et al. (2024) also indicated that the allocation of healthcare resources in some regions required further optimization. This finding is similar to the results of the present study, which confirmed the hypothesis that regional differences exist.

In a study analyzing the healthcare system reform across 31 provinces in China from 2009 to 2021, it was found that the average level of healthcare efficiency exhibited a fluctuating upward trend (Sun et al., 2023). The study by Sun et al. (2023) also identified regional disparities in healthcare efficiency within China, which aligns with the findings of the present study supporting the hypothesis of regional differences.

A study conducted across 31 provinces in China covering the period from 1997 to 2022 reported an average efficiency score of 0.7672 for the healthcare system, indicating a moderate level of efficiency (Xu et al., 2024). The Kruskal–Wallis analysis used by Xu et al. (2024) revealed significant variations in efficiency, productivity growth, and production technology among healthcare systems in Eastern, Central, Western, and Northeastern China. This is comparable to the present study, where the non-parametric Mann–Whitney U test demonstrated statistically significant differences in efficiency trends—both increasing and decreasing—across regions and years.

A study conducted across 31 provinces in China from 2012 to 2020 demonstrated a decline in the efficiency level of the primary healthcare system (Huang et al., 2024). Huang et al. (2024) found that efficiency in more developed regions was significantly higher than in less developed areas. This finding is supported by the present study, where more developed regions such as Western Marmara, Eastern Marmara, Istanbul, and Aegean exhibited higher efficiency levels compared to less developed regions like Northeast, Central East, and Southeast.

A study conducted in a municipality in southwestern China following healthcare reform revealed a slight decline in the efficiency of primary healthcare systems across the municipality between 2009 and 2018. Factors influencing the efficiency of primary healthcare systems included the urbanization rate of the region/city, per capita financial expenditure in primary healthcare institutions, and the number of nurses per 1,000 inhabitants (Zeng et al., 2024). In the present study, one of the inputs was the total number of physicians per 100,000 people. Both studies similarly highlight the presence of professional healthcare workers as a key input affecting efficiency.

Another study found that the average technical efficiency of urban primary healthcare institutions was lower than that of rural ones between 2009 and 2019 (Zhou et al., 2023). This finding contradicts the results of the present study, where more urbanized regions such as Western Marmara, Eastern Marmara, Istanbul, and Aegean exhibited higher efficiency levels compared to more rural regions like Northeast, Central East, and Southeast.

In a study comparing the efficiency of medical device utilization across 81 provinces in Türkiye, 22 provinces were found to be efficient, while 59 were inefficient (İlgün et al., 2022). The finding that Istanbul was among the efficient provinces in both the study conducted by İlgün et al. (2022) and the present study demonstrates consistency. However, there is a contradiction in that, while İlgün et al. (2022) identified 10 provinces from the Mediterranean, Southeastern, and Eastern Anatolia regions as efficient, the present study found that all provinces in these regions exhibited low total factor productivity (tfpch < 1). Similarly, the current study identified 8 provinces in the Western Marmara and Western Anatolia regions as having high total factor productivity (tfpch > 1), which contradicts the findings of İlgün et al. (2022), where all of these provinces were found to be inefficient.

In another study comparing the efficiency of medical imaging devices in Turkish hospitals for the year 2021, the lowest efficiency was observed in Doppler ultrasound devices in university hospitals, with an efficiency rate of 54%. In addition, the efficiency rate of CT and Doppler ultrasound devices in private hospitals was reported as 57%, while mammography devices were found to be fully efficient (100%) across all sectors (Yüksel, 2023). In contrast to these findings, the present study identified CT, MRI, and Doppler ultrasound as highly efficient devices, whereas ECHO and mammography were found to have lower efficiency, thereby contradicting the results reported by Yüksel (2023).

In a study conducted using 2017 data from 11 cities sampled from Henan Province in China, the efficiency indicator was found to be only 0.732, with the pure technical and scale efficiency scores of four cities in the sample falling below 1. This indicates lower MRI efficiency and an overall inefficiency in MRI utilization (Huang et al., 2023). In contrast, the average Total Factor Productivity Change (TFPCH) indicator for MRI devices in the present study was 1.026 over the period from 2013 to 2022, which contradicts the findings reported by Huang et al. (2023).

The study conducted in Italy showed that the use of newer equipment led to a decrease in productivity, and that the presence of a more senior chief radiology technician and customer satisfaction survey systems did not translate into improved productivity (Visintin et al., 2024). In contrast, the present study found technological change (techch) indicators of 1.034 for MRI devices and 1.023 for CT devices, suggesting an increase in productivity, thereby contradicting the findings of Visintin et al. (2024).

6. CONCLUSION

When evaluating the total factor productivity (TFP) indicators of medical imaging devices across regions and years, CT, MRI, and Doppler ultrasonography were found to exhibit high productivity, whereas echocardiography (ECHO) and mammography demonstrated low productivity. Cardiovascular diseases and neoplasms are known to be the leading causes of death in recent years. The consistently low productivity of ECHO devices—which play a critical role in the diagnosis and follow-up of circulatory system and various heart diseases, as well as in the early detection of myocardial infarction—over the past decade is a noteworthy finding. Similarly, the low productivity of mammography devices over the last 10 years, despite their vital role in the early diagnosis of breast cancer, particularly among women, is brought to the attention of policymakers and decision-makers.

Regions in northern and western Türkiye were found to have higher average TFP indicators for medical imaging devices, while southern and eastern regions showed lower productivity levels. Moreover, the TFP indicators for medical imaging devices did not consistently demonstrate high productivity between 2013 and 2022.

It was observed that there was a statistically significant difference between the 12 regions in the NUTS according to the low and high total factor efficiency average of medical imaging devices. Likewise, there was a statistically significant difference across Türkiye between 2013 and 2022 in terms of whether the average TFP of medical imaging devices was high or low.

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