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# Classification of medical imaging technologies: results from Türkiye

Hakan Temiz[1*] and Tuncay Kara[2]

## Abstract

**Background** Regional disparities in access to medical diagnostic imaging technologies (MDITs) present a significant barrier to achieving health equity, particularly in developing countries. Understanding how these technologies are distributed and utilized is essential for informing equitable health policy.

**Method** This study examines the distribution and utilization of MDITs across Türkiye's 12 NUTS regions using a hierarchical clustering approach. Unlike previous studies, the analysis incorporates both technological capacity and utilization (CaU) variables, evaluated jointly and independently. Imaging modalities are also stratified based on their technological complexity and investment requirements to capture nuanced regional patterns.

**Results** Findings indicate that although Türkiye demonstrates an overall balanced distribution of MDITs, notable regional disparities in utilization efficiency remain. Regions exhibiting similar usage patterns tend to cluster together irrespective of geographic proximity. Interestingly, the clusters often transcend geographical proximity; regions located at opposite ends of the country tend to cluster on the basis of similar utilization patterns. This may suggest that disparities between administrative centers and rural areas are less pronounced than previously assumed. These patterns imply that institutional capacity, healthcare workforce distribution, and demographic demand may have a stronger influence on utilization than spatial location.

**Conclusion** The study highlights a disconnect between capacity and actual use of diagnostic imaging technologies, underscoring the need for targeted policy interventions. It also suggests that regional utilization patterns may align more with functional similarities than with geographic proximity. Moreover, analyzing technological capacity and utilization variables separately—rather than as a combined index—yielded more transparent and objective insights into regional disparities. These findings contribute to optimizing health resource allocation and support evidence-based policymaking aimed at advancing equitable access to diagnostic services, aligning with Türkiye's commitment to universal health coverage.

**Keywords** Health equity, Diagnostic imaging, Regional disparities, Healthcare utilization, Hierarchical clustering, Capacity and use, Türkiye

*Correspondence:
Hakan Temiz
htemiz@artvin.edu.tr
[1]Department of Computer Engineering, Artvin Coruh University, Artvin, Türkiye
[2]Health Administration Department, Ankara, Türkiye

## Introduction

Health disparities between urban and rural areas remain a pressing issue in contemporary societies. A primary contributor to these disparities is the unequal distribution of public health resources, including healthcare professionals and medical technologies. Among these technologies, medical diagnostic imaging technologies (MDITs) play a critical role by offering noninvasive, accurate diagnostic capabilities and enabling effective monitoring of therapeutic interventions. Therefore, the equitable distribution of MDIT across all regions is essential for achieving health equity.

Ensuring equal access to high-tech medical resources and health professionals is fundamental to the realization of universal health coverage (UHC), especially in developing countries. Türkiye's Health Transformation Program (HTP), launched in 2003, marked a pivotal step toward UHC, which was fully implemented by 2009. Within this framework, the collection of reliable and timely data on healthcare personnel and medical technologies is indispensable for effective health system planning and management. Such data enable policymakers to detect and address inequalities more rapidly and precisely.

This study investigates regional disparities in MDIT distribution across Türkiye by employing hierarchical clustering methods. Although a previous study by Songur and Top [1] conducted a similar analysis using 2013 data [2], their approach jointly analyzed the capacity and utilization (CaU) variables, potentially leading to misleading interpretations due to the differing statistical characteristics of these variables. In contrast, our study evaluates CaU variables both jointly and independently while also categorizing MDIT into subgroups on the basis of technological characteristics and investment levels.

Moreover, our findings emphasize that evaluating MDIT distributions via aggregated data may obscure significant regional differences due to the heterogeneity of imaging technologies in terms of cost, utilization patterns, and technological complexity. High-tech modalities, such as magnetic resonance imaging (MRI) and computed tomography (CT), which require substantial investment and specialized operational expertise, exhibit distinct spatial and statistical characteristics compared with lower-cost devices such as ultrasonography or echocardiography. To address this, our study employs a stratified analytical approach, clustering devices on the basis of shared characteristics and analyzing CaU variables both jointly and separately. To our knowledge, this is the first comprehensive study in Türkiye that systematically analyzes CaU variables together and separately across different device groupings. This methodology enables a more refined identification of disparities, yielding results that challenge previous assumptions about regional inequality.

Our approach yielded more objective and precise insights into the distribution of MDITs, indicating that Türkiye's 12 NUTS regions can be broadly grouped into three to five clusters. The findings suggest that, with few exceptions, Türkiye presents a relatively balanced distribution of MDITs and has made considerable progress toward ensuring equitable access to diagnostic healthcare services.

Interestingly, the clusters often transcend geographical proximity; regions located at opposite ends of the country tend to cluster on the basis of similar utilization patterns. This may suggest that disparities between administrative centers and rural areas are less pronounced than previously assumed. However, our analysis of capacity utilization rates reveals regional variation: some areas exhibit moderately high utilization relative to their technological capacity, pointing to either efficient use or rising demand, whereas others demonstrate underutilization, potentially reflecting a misalignment between resource investment and actual service delivery.

These findings underscore the need for policymakers to incorporate both quantitative and qualitative indicators—such as demographic trends, regional health needs, and healthcare workforce distribution—into health system planning. By identifying discrepancies between technological capacity and actual use, this study offers valuable guidance for optimizing resource allocation and enhancing equitable access to diagnostic services across Türkiye.

### Literature

The invention of X-rays in 1895 by Wilhelm Conrad Röntgen revolutionized diagnostic techniques, marking the beginning of a new era in medical imaging [3]. Röntgen's first X-ray image of his wife's hand, which was shared around the world on Christmas Day 1895 [4], highlights the potential of this technology to examine the human body noninvasively. This discovery laid the foundation for the development of other advanced imaging techniques. In 1942, ultrasound imaging (USI) was introduced [5], followed by the advent of computed tomography (CT) in 1971 [6] and magnetic resonance imaging (MRI) in 1977 [7]. These innovations have enabled increasingly precise studies of internal body structures and the detection of diseases. The turn of the millennium saw the introduction of positron emission tomography-computed tomography (PET-CT) in 2001, which combines the functional imaging of PET with the detailed anatomical imaging of CT [8]. With PET-CT, medical imaging has advanced, becoming a critical tool for diagnosing and monitoring various diseases, and has since been adopted globally in clinical practice.

Diagnostic and therapeutic processes are closely tied to advancements in healthcare technology. The strong connection between innovation and healthcare is also recognized in legal frameworks, such as the European Union's (EU) Future and Emerging Technologies initiative [9]. Within this context, MDITs and technological innovations play a vital role in patient care. The adoption of high-tech equipment strengthens health systems [10] by increasing diagnostic accuracy, treatment efficiency, and patient outcomes while enabling early disease detection and reducing preventable mortality [11]. Their integration also optimizes healthcare resources (HRs) by minimizing unnecessary procedures and hospitalizations, thereby promoting health equity across regions [12].

Every citizen has the right to fair and timely healthcare access, yet geographic and economic disparities often hinder this right. Achieving health equity requires a balanced distribution of MDIT, along with medical professionals and facilities. Skilled radiologists and imaging technicians are as crucial as the equipment itself, as their absence in certain regions limits effective utilization. To ensure equitable healthcare access, countries must strategically distribute MDIT and other medical resources. Relying solely on factors such as population density often results in resource overconcentration in urban areas, exacerbating rural healthcare gaps. Instead, distribution should be guided by a comprehensive approach that considers disease prevalence, regional demand, and emergency response needs.

The distribution of MDIT directly impacts access to diagnostic services, healthcare equity, and overall patient outcomes. Several methods have been employed to analyze the spatial distribution, accessibility, and effectiveness of MDITs, ranging from statistical analyses to geographic information system (GIS) and optimization models. These methods are essential for understanding how resources are allocated across regions and identifying disparities in healthcare access.

#### *Statistical methods for cluster analysis*

Cluster analysis is frequently applied to identify groups of regions or facilities with similar access to resources [1, 13, 14]. Methods such as k-means clustering, hierarchical clustering, and the use of distance measures, e.g., Euclidean or Manhattan distances, are commonly employed to classify areas on the basis of equipment availability, healthcare quality, and service utilization [15]. Z score standardization is often used prior to cluster analysis to normalize the data and account for variations in scale across different regions or healthcare settings. These analyses can provide valuable insights into the concentration of MDITs and highlight areas that may require further intervention. This study employed a statistical and spatial approach for cluster analysis.

#### *Spatial analysis and Geographic Information Systems (GIS)*

GIS is widely used to analyze the spatial distribution of healthcare resources, as it allows for visualizing the locations of imaging equipment in relation to population density, disease prevalence, and healthcare facilities [16–19]. Researchers use GISs to map areas with limited access to MDITs, particularly in rural or underserved regions [20]. By overlaying demographic data and healthcare infrastructure, GIS-based approaches help identify gaps in access and optimize resource distribution. Furthermore, spatial clustering techniques can reveal geographic patterns of healthcare access and utilization, aiding policymakers in addressing regional disparities. Chandran and Roy [21], Khashoggi and Murad [18] and Neutens [22] serve as valuable starting points for readers seeking comprehensive insights into GIS applications for healthcare accessibility.

#### *Big data and machine learning approaches*

In recent years, big data analytics and ML techniques have gained traction in the analysis of HR distributions [23, 24]. By analyzing large-scale healthcare datasets, these methods can uncover hidden patterns and trends in the utilization and allocation of MDITs. Predictive modeling and clustering algorithms, such as random forests and support vector machines, are employed to forecast the demand for MDITs in various regions and recommend optimal distribution strategies. These advanced techniques allow for more dynamic and real-time assessments of healthcare infrastructure and can help predict future needs on the basis of demographic and epidemiological trends [25].

#### *Optimization models for resource allocation*

Optimization techniques are utilized to determine the most efficient allocation of HRs across regions. Linear programming [26], mixed-integer programming, and heuristic algorithms have been applied to solve problems related to the optimal placement of imaging equipment, ensuring that resources are distributed equitably on the basis of factors such as population needs, disease burden, and geographical constraints [27, 28]. These models seek to minimize disparities in healthcare access by strategically positioning MDITs where they are needed most, often factoring in cost-effectiveness and resource constraints.

#### *Equity assessment and policy analysis*

Another common approach in distribution analysis is the evaluation of healthcare equity, which focuses on how MDITs contribute to reducing health disparities. Equity indices, such as the Gini coefficient [29, 30], concentration index [12, 31, 32], Herfindahl‒Hirschman index [29, 33], Atkinson index [34], Malmquist productivity index

(MPI) [35], Theil index [12, 36] and Lorenz curve [37], are employed to measure the evenness of distribution across different population groups. Studies also use regression models [38] to analyze the relationship between the availability of MDITs and health outcomes, examining whether disparities in access lead to differences in preventable mortality rates or diagnostic accuracy. Policy analysis frameworks often involve scenario modeling to evaluate the effectiveness of different distribution strategies, helping policymakers identify interventions that promote more equitable healthcare access.

Türkiye launched the HTP in 2003, but it has been collecting medical technology data for distribution only in the past decade. At the time of this study, the only significant research examining inequalities in MDIT distribution across Turkey's 12 regions was conducted by Songur and Top [1]. The authors noted regional disparities in hospital ownership and MDIT distribution on the basis of their analysis, which included CaU data. However, because these variables have distinct characteristics and provide different types of information, combining them may lead to misleading conclusions about inequalities. Several factors, such as varying socioeconomic structures and disease burdens, affect the utilization of these technologies. For example, regional hospitals may have high-tech equipment and larger capacities but still experience lower patient admissions than they can accommodate. Therefore, treating these disparate variables as a single set can lead to inaccurate results. To address this issue, we analyzed the data separately for each variable and on a per-device basis.

## Data and method

Eurostat and Türkiye defined 3 levels for statistical analysis. Türkiye announced the Nomenclature of Territorial Units for Statistics (NUTS) data in 2002. NUTS is based on the following three criteria: (i) geographical characteristics of the region, (ii) socioeconomic potential (e.g., intensive agricultural activities) and (iii) population. According to the state's definition, levels 1 to 3 correspond to 3 million, 800,000 and 150,000 populations and 12, 26 and 81 NUTS regions, respectively [39]. The NUTS-1 regions are as follows: Mediterranean, Western Anatolia, Western Black Sea, Western Marmara, Eastern Black Sea, Eastern Marmara, Aegean, Southeastern Anatolia, Istanbul, Northeastern Anatolia, Central Anatolia and Central Eastern Anatolia [40].

Countries base the allocation of MDITs on the population to ensure equity in health access, as the most expensive MDIT technologies are MRI and CT. Therefore, NUTS-1 regions have been considered to obtain a high-level view of the MDIT distribution. Table 1 presents all the variables introduced in the analyses. The former 6 are used for assessing capacity, and the latter are used for the use of MDIT. As mentioned above, CaU variables provide different information on the subject. For example, when the capacity is high but technology applications are low, the use value would then be low, and vice versa.

We evaluated regional inequalities in MDIT distribution across all health units in Turkey, including university, private, and public hospitals. The data were sourced from the statistical yearbooks of the Turkish Ministry of Health for the years 2013 [2] and 2018 [41]. Capacity and usage data were obtained from Chapters 7 and 8, respectively. As the data were complete, no further data completion was necessary.

We conducted seven distinct analyses in our study. First, we analyzed the capacity and usage data for the years 2013 and 2018 via hierarchical clustering to establish a basis for comparison with the literature. To focus exclusively on the most recent data, subsequent analyses were performed solely for the year 2018. In these analyses, each variable was considered separately and subjected to three different approaches: all the data were combined, the MR and CT data were grouped together, and the US, DUS, MAM, and ECO data were grouped into another set. The characteristics of MR and CT devices, such as their technology and cost, differ significantly from those of other devices and can influence investment decisions regarding their allocation. As such, these devices were analyzed separately. To the best of our knowledge, this is the first study to examine all CaU variables both together and separately. The seven different variable sets are presented in Table 2.

Z score standardization was applied before the analysis, using Euclidean distance, in line with literature. This ensures reliable comparisons and maintains continuity in tracking development over time. The formula for calculating the Euclidean distance D between two regions, A and B, based on a given set of devices is as follows:

**Table 1** Capacity and utilization indicators for medical diagnostic imaging technologies

| |
|---|
| Medical imaging technology capacity rates (per million inhabitants) |
| V1. Number of Magnetic resonance imaging (MRI) units |
| V2. Number of Computed Tomography (CT) units |
| V3. Number of Ultrasonography devices |
| V4. Number of Doppler Ultrasonography (DUS) devices |
| V5. Number of Mammography devices |
| V6. Number of Echocardiography (ECO) devices |
| Medical imaging Technology use rates (per thousand inhabitants) |
| V7. Number of MRI exams |
| V8. Number of CT exams |
| V9. Number of Ultrasonography exams |
| V10. Number of Doppler Ultrasonography (DUS) exams |
| V11. Number of Mammography exams |
| V12. Number of Echocardiography (ECO) exams |

**Table 2** Variable sets for capacity and utilization analysis of diagnostic imaging technologies

| No | Variables | Analytical Focus | Technology |
|---|---|---|---|
| 1 | V1 to V12 | Capacity and Use | All |
| 2 | V1 to V6 | Capacity | All |
| 3 | V1 to V2 | Capacity | MRI and CT |
| 4 | V3 to V6 | Capacity | US, DUS, MAM, ECO |
| 5 | V7 to V12 | Use | All |
| 6 | V7 to V8 | Use | MRI and CT |
| 7 | V9 to V12 | Use | US, DUS, MAM, ECO |

$$D\left(A,B\right)=\sqrt{\sum\nolimits_{i=1}^{n}\left(X_{A,i}-X_{B,i}\right)^{2}} \tag{1}$$

Where, $X_{A,i}$ and $X_{B,i}$ are the values of the i-th device for regions A and B, respectively, and n is the total number of devices in the group.

Z score standardization calculates the deviation of each data point from the mean by dividing the difference between the data point and the mean by the standard deviation of the dataset. The goal is to transform the data into a standard normally distributed set with a mean of 0 and a standard deviation of 1. This type of standardization is crucial in preanalysis clustering, as it ensures consistent scaling and comparison across variables [42]. The formula of Z score standardization is as follows:

$$Z=\frac{\mathrm{X}-\mu}{\sigma} \tag{2}$$

Where, X is the individual data point, μ is the mean of the dataset, and σ is the standard deviation of the dataset. The standard deviation measures the spread of the data and is calculated as follows:

$$\sigma=\sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(X_{i}-\mu\right)^{2}} \tag{3}$$

Rather than focusing on individual specializations, we examined the overall similarities and differences in the data by analyzing the distances between individuals [43]. The distances were scaled to the range of 0–25 to easily identify clusters. We used IBM SPSS 21 software for all the experiments, except for determining the optimal number of clusters, where we employed R with the NbClust package.

We applied Ward's method for hierarchical clustering, which calculates distances between clusters via analysis of variance. Unlike other linkage algorithms, it successively merges the closest or most similar objects to minimize the overall cluster variance [42]. Its variance-minimizing property enables the formation of tight, homogeneous clusters, making it particularly effective for heterogeneous datasets with high variability, such as medical imaging technologies such as MRI, CT, and X-ray. Additionally, the method produces meaningful, compact clusters, simplifying the interpretation of complex patterns and groupings. This enhances analysis and aids in the categorization of technologies for clinical, operational, or distribution-based insights.

## Results

Appendix A presents the descriptive statistics of the data along with visualizations. Notably, the US and DUS variables present significantly greater means and standard deviations than the other variables do. Additional findings are discussed in the appendix.

There are various methods for clustering validation [44], including majority voting, the elbow method, silhouette analysis, the Davies–Bouldin index, the Calinski–Harabasz index, and the Dunn index, among others. The optimal number of clusters was determined via majority voting across 27 indices with the "NbClust" package in the R environment [45]. The overall voting results, along with the votes from each index for a specific set of variables, are presented in Table 1 in Appendix B.

### Joint analysis by capacity and use variables

In the first analysis, we included all the CaU variables separately for both the 2013 and 2018 data. Table 1 in Appendix D shows the Euclidean distances between regions obtained from the 2018 data. We do not present the distances calculated for the 2013 data [2] again, as they were already provided in a previous study [1]. However, we observed that some values were incorrectly taken from the annual data in the previous study. Therefore, in our analysis of the 2013 data, differences were observed in some of the clusters obtained from the previous study. The incorrect values and their correct equivalents are shown in Table 1 in Appendix C. We present the updated dendrogram with the actual values for the 2013 data in Fig. 1(a) and for the 2018 data in Fig. 1(b).

The greatest distance (86.098) is observed between the Istanbul and Southeastern Anatolia regions, followed by Southeastern Anatolia and Western Anatolia (65.046). In contrast, the shortest distance (9.277) is recorded among the Eastern Black Sea, Eastern Marmara, and Western Marmara regions.

Table 2 in Appendix C presents the results of the cluster analysis for both 2013 (including previous and updated analyses) and 2018. In addition to the clusters identified in the previous study, the table includes the results of a reanalysis performed using the actual values for 2013.

Between 2013 and 2018, the clustering distribution of Türkiye's NUTS regions demonstrated a positive trend toward regional convergence and integration. In 2013, five distinct clusters reflected considerable regional

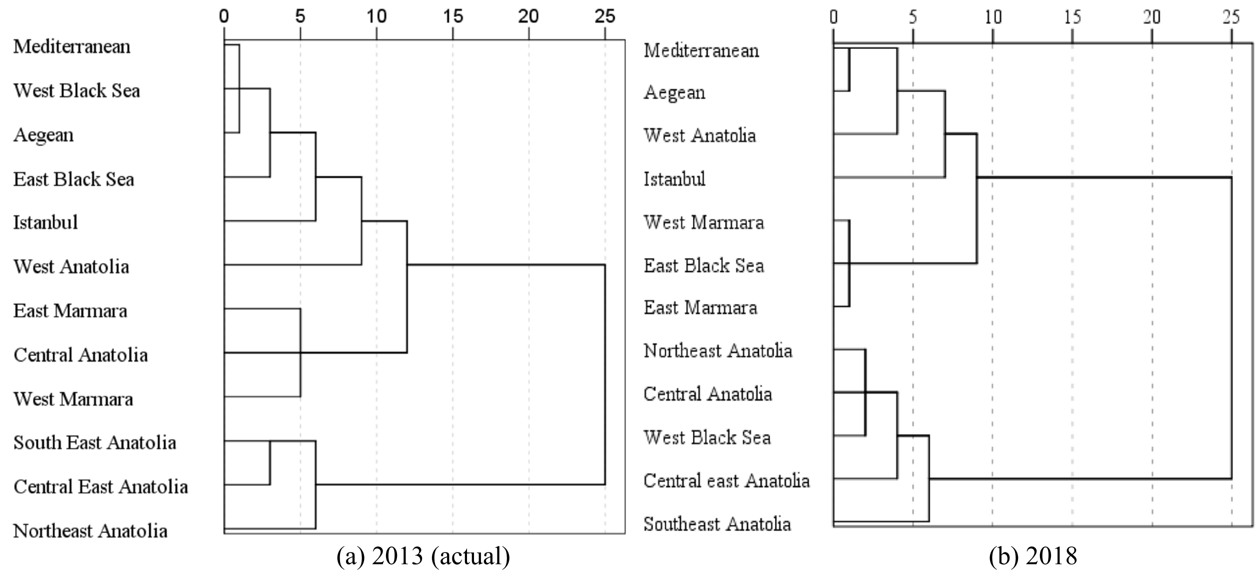


**Fig. 1** Hierarchical clustering dendrograms based on all CaU variables for 2013 (**a**, using actual values) and 2018 (**b**)

diversity, with some regions—such as Istanbul and Western Anatolia—forming standalone clusters, and Eastern and Southeastern Anatolia grouped separately, indicating varying development characteristics. By 2018, this fragmented structure had transitioned into a more cohesive pattern with only two clusters. The western and coastal regions, including Istanbul, Aegean, and Mediterranean, were grouped into a single cluster, suggesting a growing alignment in terms of socioeconomic and infrastructural indicators. At the same time, Central, Eastern, and Southeastern Anatolia displayed increased internal similarity by forming a unified cluster. This reduction in the number of clusters can point to a general trend of harmonization across regions, likely influenced by national development efforts and improved regional integration. Overall, the clustering results highlight meaningful progress toward a more balanced and cohesive regional structure across the country. Additionally, it was previously stated that the easternmost regions—Central Anatolia, Southeastern Anatolia, Northeastern Anatolia, and Eastern Anatolia—formed a single cluster. However, on the basis of the 2018 analysis, we disagree with this conclusion, as some of these regions are now grouped with western regions. Specifically, the Eastern Black Sea region is clustered with the Western and Eastern Marmara regions in the west of the country, whereas the Western Black Sea region is grouped with Central Anatolia, Northeast Anatolia, and Eastern Anatolia. Contrary to previous studies, we can conclude that there is no significant distinction between the eastern and western parts of the country. Additionally, as will be shown later, it should be noted that the results of this analysis, which was conducted with the internal data of all devices, are insufficient for accurately reflecting reality.

It can be argued that the main reason for the difference observed in clusters between 2013 and 2018 is the government's policies aimed at supporting health tourism. Specifically, Istanbul, the most populous city, serves as both the financial center and the industrial heart of Türkiye. However, owing to its attractive features—such as its rich history, geography, and advanced healthcare facilities—it attracts a significant number of tourists, particularly those visiting for health tourism. Additionally, the Mediterranean region, where Antalya is located, and the Aegean region are among the top tourist destinations. Consequently, these factors have led the government to implement specific policies for health tourism in these regions, resulting in an increase in device capacity in these regions compared with other regions.

CaU variables should be analyzed separately because capacity variables reflect the amount of MDIT equipment, whereas usage variables can be influenced by factors such as patient load, socioeconomic conditions, and physicians'circumstances. By separating these two variables, we can gain a clearer understanding of the situation. Therefore, unlike previous studies [1], we differentiated both variables in our subsequent experiments.

### Analysis by capacity variables

Table 2 in Appendix D presents the results of the subsequent analysis, which was conducted using only the capacity variables (V1 to V6). Figure 2 shows the corresponding dendrogram. As observed in the previous analysis, the longest distance (47.142) was recorded between the Southeastern Anatolia and Istanbul regions. Conversely, the shortest distance was observed between the Central Eastern Anatolia, Western Black Sea, and Eastern Marmara regions.

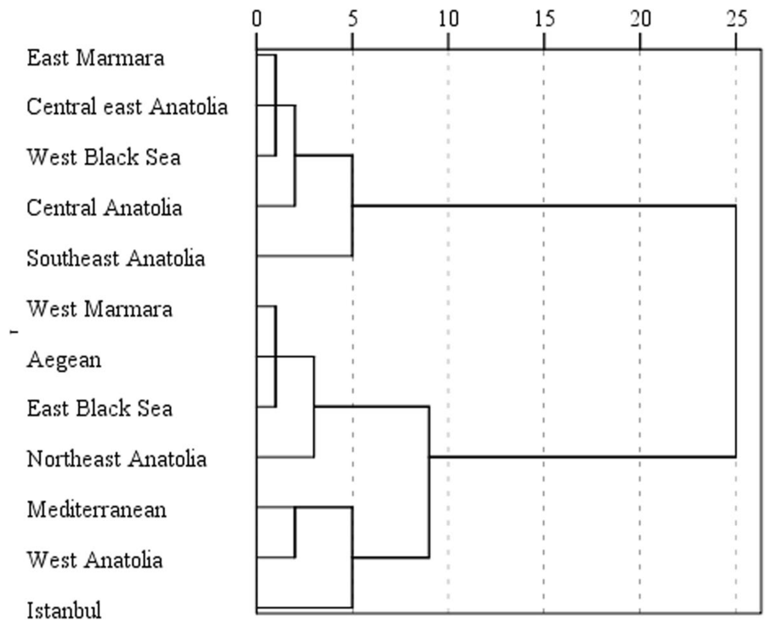


**Fig. 2** Dendrogram of hierarchical clustering based on capacity variables V1 to V6

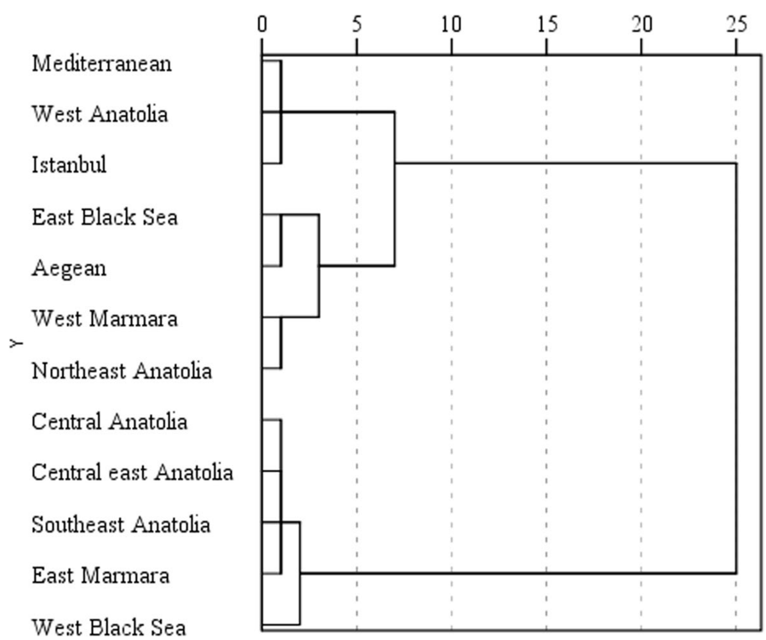


**Fig. 3** Dendrogram of hierarchical clustering based on capacity variables V1 (MRI) and V2 (CT)

The regions can be categorized into three clusters. The western regions are grouped together with the northeastern regions of the country. The southern regions (excluding Southeastern Anatolia), Istanbul, and Western Anatolia form the second cluster, whereas the remaining regions constitute the third cluster.

Compared with other technologies, CT and MRI technologies have distinct characteristics, particularly in terms of technology and pricing. Therefore, they should be considered separately, as the statistics on their distribution and prevalence differ significantly from those of other technologies. To address this, we conducted a separate analysis focusing exclusively on these two technologies. The proximity matrix is presented in Table 3 of Appendix D, and the corresponding dendrogram is shown in Fig. 3. The Western Anatolia and Mediterranean regions were the closest to each other (0.006), while the Mediterranean and southeastern regions were the farthest away (13.277). The regions should be separated into two main groups according to the clustering metrics. The eastern and southeastern regions of the country form a cluster with the northern and northwestern regions, whereas the northeastern regions form a separate cluster with the Mediterranean and western regions.

If the cutoff point is shifted to approximately 5, three main clusters are formed. In this case, the Mediterranean, Western Anatolia, and Istanbul regions were grouped together in the first cluster. The second cluster consists of the Central Anatolia, Central Eastern Anatolia, Southeastern Anatolia, Eastern Marmara, and Western Black Sea regions, whereas the third cluster includes the Eastern Black Sea, Aegean, Western Marmara, and Northeastern Anatolia regions. The Mediterranean and Eastern Black Sea regions would be the closest to each other, whereas the Western Anatolia and Southeastern Anatolia regions would be the farthest apart.

In the fourth analysis, we considered the capacity variables of US, DUS, MAM, and ECO. These devices were considered together owing to their use of similar, low-technology techniques compared with MRI and CT. The results are presented in Table 4 in Appendix D, with the corresponding dendrogram shown in Fig. 4. Three regions are observed in this analysis. While the Istanbul and Western Anatolia regions are grouped together, the eastern and southeastern regions of the country are placed in the same cluster as the northern and northwestern regions. The Northeastern Black Sea region, on the other hand, forms the final cluster with the Mediterranean and western regions of the country.

**Analysis by use variables**

In the next analysis, we focused solely on the usage variables (V7 to V12). The calculated distances between the regions are presented in Table 5 of Appendix D, with the corresponding dendrogram shown in Fig. 5. The longest distance was measured between the Istanbul and Southeastern Anatolia regions, whereas the shortest distance was observed between the Central Anatolia and Northeastern Anatolia regions.

This time, the regions are grouped into three clusters again, but with a slightly different distribution compared with the analysis of the capacity variables of the same technologies. The Marmara region, which is home to more than a quarter of Turkey's population, consists of three NUTS-1 regions: Eastern Marmara, Western Marmara, and Istanbul. According to the analysis, the entire Marmara region is grouped with the Black Sea region in the same cluster. The Western Black Sea and Central Eastern Anatolia regions are combined with the Mediterranean and Western regions of the country. The final cluster includes the Central and Northern Anatolia regions, along with Southeastern Anatolia.

Another analysis was conducted for the usage values of MR images and CT images together. The results are presented in Table 6 in Appendix D and Fig. 6. According to the clustering metrics, this analysis results in the highest number of clusters—specifically, five. The distances between the regions are notably smaller. The greatest and smallest distances are observed between the Central Anatolia and Istanbul regions (15.269) and between the Mediterranean and Aegean regions (0.044), respectively. Interestingly, Northeastern Anatolia is grouped in the

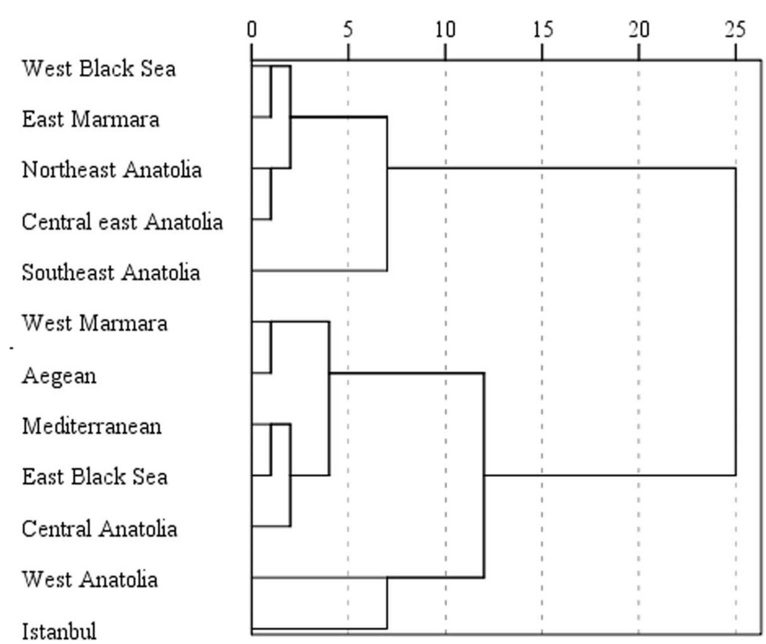


**Fig. 4** Dendrogram of hierarchical clustering based on capacity variables V3 (US), V4 (DUS), V5 (MAM) and V6 (ECO)

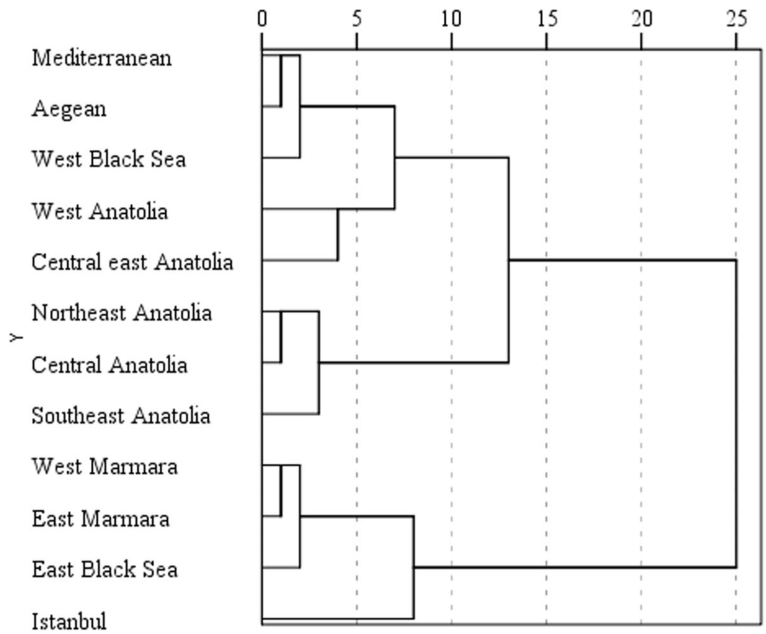


**Fig. 5** Dendrogram of hierarchical clustering based on use variables V7 to V12

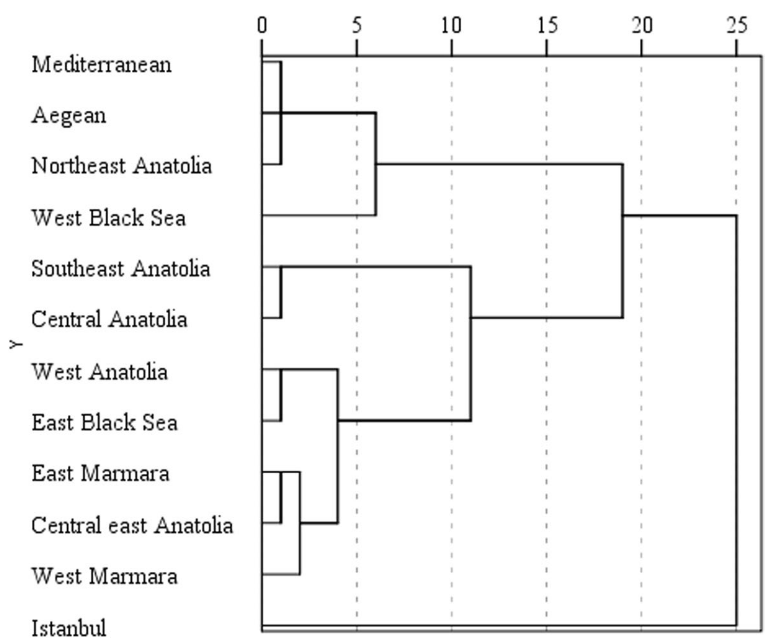


**Fig. 6** Dendrogram of hierarchical clustering based on use variables V7 (MRI) and V8 (CT)

same cluster as the Mediterranean and Aegean regions. On the basis of visual examinations, a distribution with fewer clusters may be observed. However, at this point, we prefer to adhere to the decision on the number of clusters, as determined by the majority of the clustering distribution criteria. In all the cases, Istanbul is significantly separated from the other regions.

In the final analysis, we evaluated the regions using the US, DUS, MAM, and ECO variables. The proximity matrix and dendrogram are presented in Table 7 in Appendix D and Fig. 7, respectively. The regions are once again grouped into three main clusters. The shortest distance was observed between the Aegean and Western Black Sea regions, followed by the distance between Northeastern Anatolia and Central Anatolia. The greatest distance is between Istanbul and Southeastern Anatolia. As observed in most of the previous analyses, the Eastern Black Sea region is grouped in the same cluster as the regions located in the Marmara region, despite being approximately a thousand kilometers away.

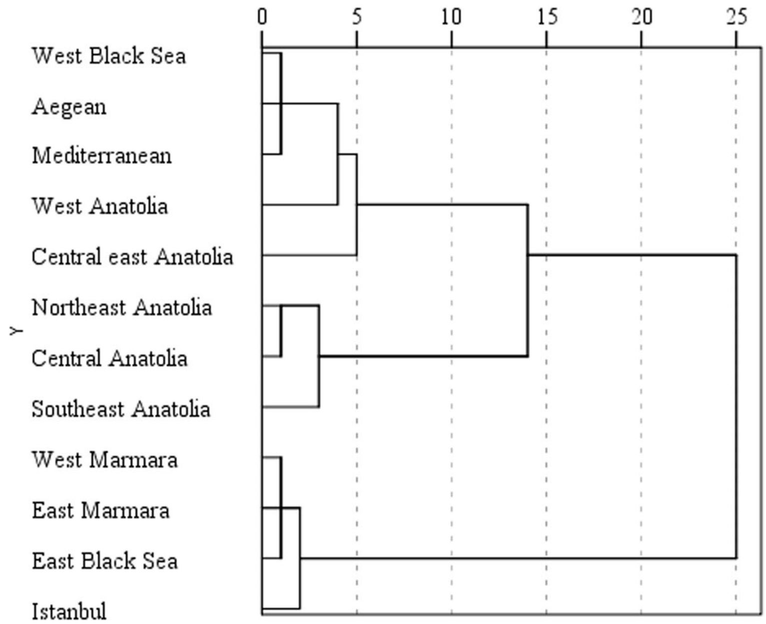


**Fig. 7** Dendrogram of hierarchical clustering based on use variables V9 (US), V10 (DUS), V11 (MAM) and V12 (ECO)

## Discussion

The following subsections discuss our cluster analysis approach to the distribution of MDIT and Türkiye's access to healthcare services.

### Our approach to clustering analysis

Each MDIT exhibits distinct characteristics in terms of clinical application, conditions, utilization rates, and levels of investment. Consequently, not all aspects of MDIT data uniformly reflect the broader healthcare landscape. For example, a private hospital may possess a disproportionately high number of MRI and CT scanners, which could indicate substantial financial capacity and a more extensive service network. Regional disparities in MDIT distribution are also influenced by varying public health structures, including differences in disease burden, demographic profiles, and socioeconomic conditions. Additionally, the availability of specific modalities across regions is shaped by their technological complexity and cost. Lower-cost and less technologically intensive devices—such as US and ECO—tend to be more widely accessible, whereas high-cost, advanced modalities such as CT and MRI are often concentrated in central urban areas, with limited or no presence in rural settings.

Given the substantial differences in usage patterns, technological complexity, and investment levels across devices, analyzing MDIT data as a single aggregate can lead to distorted results. For example, the statistical distance between MRI and CT is relatively small, whereas the distance between US and DUS is considerably larger, reflecting substantial differences in their variances (see Appendix A). The inclusion of variables with such divergent statistical properties in a unified analysis can skew clustering outcomes and obscure meaningful patterns. To mitigate these effects, we supplemented the overall analysis with two targeted subanalyses: one focusing on high-cost, high-complexity modalities (CT and MRI) and the other on lower-cost, more widely available technologies (US, DUS, MAM, and ECO). This stratified approach reduces the influence of variance-induced distortion and facilitates more robust and interpretable clustering results—ultimately offering a more accurate reflection of the spatial distribution of healthcare technology than approaches adopted in previous studies.

When all the variables are included in the analysis, the resulting clustering reveals a sharp east–west divide across the country. However, when the analysis is conducted on the basis of individual technologies, a more nuanced and granular clustering pattern emerges—yielding more moderate, specific, and realistic insights into regional disparities. This shift in clustering outcomes underscores the importance of addressing heterogeneous MDITs.

### Overview of the regions

Istanbul, as the country's economic and financial hub, has the highest levels of infrastructure, technological adoption, and service availability. It plays a central role in international trade, finance, tourism and industry and hosts a dense concentration of healthcare facilities (health tourism as well), educational institutions, and private enterprises. Its strategic location enhances its role in international trade and investment. Western Anatolia**,** which encompasses Ankara and Konya**,** features a balanced structure. Ankara, as the capital city, is the administrative and political center of Türkiye and stands out for its robust public services, institutional capacity, and significant investments in industrial growth and healthcare**,** whereas Konya contributes through its strong agricultural sector, complemented by a rapidly expanding industrial base, with notable growth in the manufacturing and automotive industries.

The Aegean and Mediterranean regions of Türkiye are among the more developed parts of the country, each with distinct socioeconomic profiles shaped by their geography, industry, and tourism potential. The Aegean region benefits from a diversified economy supported by agriculture, manufacturing, and a strong tourism sector. Cities such as İzmir serve as economic and cultural hubs, with well-developed infrastructure, high urbanization rates, and relatively high standards of living. The region also has significant industrial zones and ports that facilitate domestic and international trade. The Mediterranean region, particularly around cities such as Antalya, Adana, and Mersin, is marked by a dynamic tourism industry and fertile agricultural lands. Coastal areas in the western part of the region tend to be more developed, largely due to international tourism and real estate investments. However, the eastern Mediterranean still shows regional disparities in infrastructure and service accessibility compared with the western Mediterranean. Overall, both regions exhibit high levels of development, with the Aegean region being slightly more balanced across sectors, whereas the Mediterranean region's development is more concentrated in tourism and coastal urban centers.

The Western and Eastern Black Sea regions are both shaped by their agricultural and natural resource-based economies. The Western Black Sea thrives on hazelnut, tobacco, and fruit production alongside coal mining and manufacturing. Its strategic location supports maritime trade, and ecotourism is emerging due to its rich landscape. The Eastern Black Sea, known for its mountainous terrain, is focused on tea and hazelnut production, particularly in Rize. While less industrialized, the region's economy relies on agriculture, fishing, forestry, and maritime activities, and the importance of ecotourism is increasing. Both regions highlight the synergy between traditional industries, natural resources, and tourism development.

The Western Marmara and Eastern Marmara regions of Turkey each contribute uniquely to regional development. Western Marmara's economy is driven by agriculture, particularly for grains, sunflowers, and vegetables, alongside a growing automotive and manufacturing sector. Its proximity to Istanbul enhances trade, transportation, and tourism, especially coastal and historical attractions. In contrast, Eastern Marmara is an industrial hub that excels in automotive, machinery, and textiles and is supported by strong infrastructure. Agriculture, notably fruit cultivation, and a diverse tourism sector, including cultural, historical, and nature-based attractions, remain key to the region. Both regions play crucial roles in Turkey's economic structure, combining industrial, agricultural, and tourism development.

Central Anatolia stands as a significant economic hub in Turkey, driven primarily by agriculture, especially the cultivation of wheat, barley, and sugar beets. Additionally, Central Anatolia is becoming a focal point for energy investments, particularly in renewable energy sources such as wind and solar power, owing to its vast, open plains and favorable conditions. Central Eastern Anatolia, characterized by a more arid and rugged landscape, is heavily dependent on agriculture, particularly grain production, livestock, and pulse cultivation. The region also faces challenges related to water resources, which affect agricultural productivity. However, it is experiencing significant development in infrastructure, driven by regional investments in transportation and logistics. Although less industrialized than other regions, Central Eastern Anatolia is seeing an uptick in the development of small-scale industries and the expansion of agro-processing businesses.

Compared with other regions of Turkey, Northeastern Anatolia, which is characterized by mountainous terrain and a harsh climate, has a less industrialized economy. Agriculture remains the dominant sector, with a focus on animal husbandry, particularly cattle and sheep, and the cultivation of cereals and vegetables. The region is rich in natural resources, including minerals and forestry, although industrial development remains limited. Nevertheless, Northeastern Anatolia is home to growing tourism potential, particularly nature-based tourism and cultural heritage tourism, owing to its historical sites and scenic landscapes. Infrastructure improvements, particularly in transportation and healthcare, are gradually increasing a region's connectivity and quality of life.

Southeastern Anatolia, one of the most economically diverse regions of Turkey, is characterized by a blend of agriculture, industry, and services. The region is known for its large-scale irrigation projects, such as the Southeastern Anatolia Project (GAP), which have transformed it into a key agricultural producer, particularly for cotton, pistachios, and vegetables. Southeastern Anatolia also benefits from a burgeoning industrial base, particularly in textiles, machinery, and food processing. Additionally, the region's growing tourism sector, which is focused on cultural heritage and historical sites, contributes to its economic diversification. Infrastructure investments, including improvements in education and healthcare, are essential for supporting a region's long-term growth.

### Spatial analysis

Figure 8 provides a geospatial overview of all seven analyses generated via the Folium package in Python. In the titles, the symbol'#' denotes the corresponding analysis number as presented in the visualizations. In Analysis 1, which includes all the variables, the country is divided into two distinct clusters aligned almost perfectly along an east–west axis—with the notable exception of the Eastern Black Sea (EBS) region. However, in the more nuanced Analyses 2 through 6, which consider the specific characteristics of the technologies, geographically distant regions are often grouped together, revealing more complex patterns of association. These analyses generally yield three well-balanced and inclusive clusters, suggesting a more homogeneous distribution across the country.

The Mediterranean (MED) and Aegean (AEG) regions consistently cluster together across most analyses, whereas Western Anatolia (WA) joins this cluster in four analyses. The Eastern Black Sea region also occasionally appears in association with these regions. This region consistently clustered with the western and/or northwestern parts of the country across all analyses. Notably, it exhibited a persistent association with the Western Marmara (WM) region in every analysis. The eastern and southeastern regions of the country are frequently grouped with Central Anatolia (CA), Eastern Marmara (EM), and the Western Black Sea (WBS) regions.

Interestingly, the Eastern Marmara region—despite its geographic location between Istanbul and the Western Anatolia region, which encompasses the nation's capital—seldomly appears in the same cluster as both regions do. Instead, it frequently appears in the same cluster as regions from the eastern and southeastern parts of the country. Southeastern Anatolia (SA) is strongly associated with Central Anatolia, followed by the Northeastern Anatolia (NA) and Central Eastern Anatolia (CEA). It also occasionally clusters with the Eastern Marmara region. The frequent clustering of Southeastern Anatolia with Central Anatolia and other more developed regions—particularly in the western and northwestern parts of Türkiye—suggests that there is no significant disparity in access to healthcare resources between the southeastern region and the more central and developed areas of the country.

In terms of high-tech MRI and CT devices (Analyses 3 and 6), regions in both the eastern and western parts of the country are observed to cluster together. In terms of capacity (Analysis 3, with two clusters), the northeastern regions are grouped with the southern (Mediterranean) and western regions. Similarly, the southeastern regions appear in the same cluster as the northwestern and central regions. This distribution indicates that the availability of high-tech medical equipment is relatively homogeneous, even across geographically distant regions. A similar pattern is observed in terms of utilization rates (Analysis 6, with five clusters), where distant

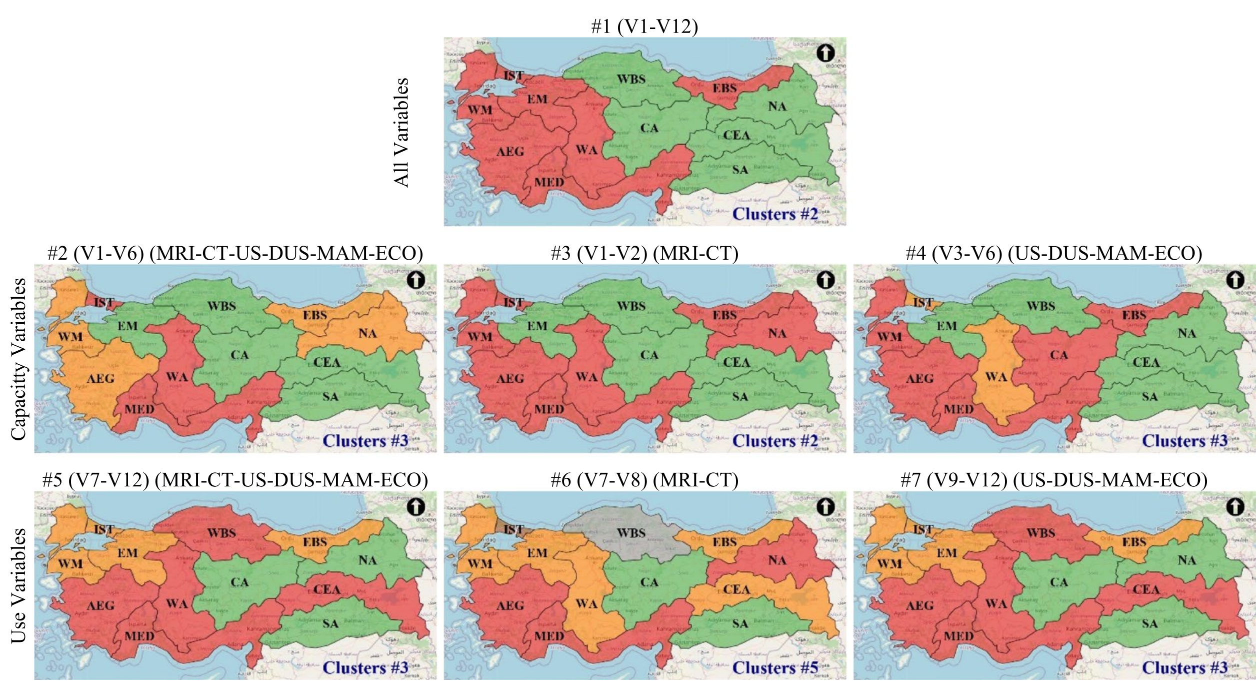


**Fig. 8** GIS representation of clustering analyses across Türkiye's NUTS regions. Abbreviations: AEG– Aegean, CA– Central Anatolia, CEA– Central Eastern Anatolia, EBS– Eastern Black Sea, EM– Eastern Marmara, IST– Istanbul, MED– Mediterranean, NA– Northeastern Anatolia, SA– Southeastern Anatolia, WA– Western Anatolia, WBS– Western Black Sea, WM– Western Marmara

regions from opposite ends of the country are found within the same clusters. However, in this analysis, Istanbul (IST) and the Western Black Sea region each form single clusters. It is well known that Istanbul's healthcare technology availability is significantly greater—or structurally distinct—than that of other regions. This is likely due to its high population density, concentration of specialized hospitals, and role as a referral center for complex diagnostics and health tourism. Consequently, Istanbul likely leads in both per capita and total availability of advanced modalities such as MRI and CT scanners.

For low-cost and less technologically intensive devices—US, DUS, MAM and ECO—the results from Analyses 4 and 7 reveal consistent regional clustering patterns in both capacity and utilization analyses. In Analysis 4, Istanbul and Western Anatolia form one cluster; the northeastern, central inland, and western regions constitute a second cluster; and the southeastern and northwestern regions constitute the third cluster. In Analysis 7, the cluster distribution differs notably. The southwestern and central-western regions form a cluster, along with the northern (Western Black Sea) and eastern (Central Eastern Anatolia) regions. Istanbul forms a distinct cluster with its neighboring regions, Western Marmara and Eastern Marmara, and notably with the Eastern Black Sea region. The final cluster included Southeastern Anatolia, Central Eastern Anatolia, and Northeastern Anatolia.

#### Access to health services in Türkiye

As a developing country, Türkiye is making continuous investments in health tourism with the goal of becoming a regional leader in this sector. In this context, Istanbul, Western Anatolia, Aegean, and Mediterranean regions, which house the majority of the population, have attracted significant private investments in health tourism. These regions are generally considered more economically developed and urbanized, suggesting a commonality in socioeconomic indicators such as income, infrastructure, tourism activity, or employment patterns captured by the selected variables. Notably, Western Anatolia, Mediterranean, and Aegean regions often form a distinct cluster, likely reflecting their economic and demographic characteristics as well as their level of investment in tourism and health tourism. Interestingly, the Eastern Black Sea region frequently aligns with these regions, suggesting a relatively high capacity, potentially due to its political representation and influence on national governance. Over the past four decades, several presidents, prime ministers, and health ministers in Türkiye have hailed from the Eastern Black Sea region, which may help explain why, despite its rural nature, this region has a similar MDIT capacity to that of more developed regions, such as the Mediterranean and Western parts of the country.

Population dynamics and growth rates play critical roles in the distribution of health services. They vary significantly across regions, and industrialization is unevenly distributed. For example, Southeastern Anatolia has experienced rapid population growth, which may lead to challenges in the coming decades, as regional capacity lags behind growth due to insufficient government investment and bureaucratic inefficiencies. Additionally, migration and asylum influxes have contributed to uneven population growth, directly impacting the distribution of MDIT. Türkiye has received the greatest number of immigrants and refugees in the past decade, resulting in irregular population shifts, particularly in Southeastern Anatolia, where many migrants initially settle. This exacerbates the region's already high population growth rate, potentially intensifying capacity issues. Over time, these population shifts have led to increasing concentrations in megacities and specific areas, further disrupting the regional balance of MDIT capacity. Moreover, varying health needs across regions, met primarily through state resources, influence public health investments and contribute to disparities in the regional availability of MDIT. While the impact of migration on these variables is beyond the scope of this study, it presents an important area for future research.

In the analyses, Southeastern Anatolia, which hosts the majority of settled minorities, is frequently clustered with Central Anatolia and Northeastern Anatolia, indicating comparable levels of development despite their relative lack of industrialization. Interestingly, these regions also moderately align with other areas located in the northern and northwestern parts of the country, such as the Western Black Sea and Eastern Marmara. In fact, especially in terms of capacity values, the regions of the country tend to cluster diagonally in the southeast–northwest and northeast–southwest directions. Therefore, the eastern and southeastern regions are frequently clustered with the geographically distant western and southwestern (Mediterranean) regions; similarly, the northeastern regions are clustered with the southwestern regions. This observation highlights a notable similarity between these regions, despite their geographical distance and positioning at opposite extremities. This clustering pattern indicates that they share key characteristics with these more developed regions, including higher levels of economic development, income, sociocultural advancement, and administrative significance. This finding challenges previous studies by suggesting that the disparity between administrative regions and those with high concentrations of ethnic minorities may not be as pronounced as previously assumed. However, this should not be

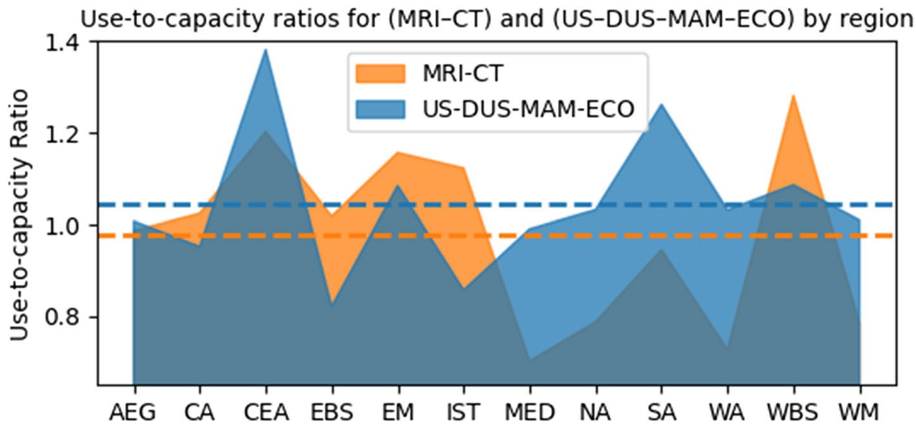


**Fig. 9** Use–to-capacity ratios for high-tech (MRI–CT) and low-tech (US–DUS–MAM–ECO) devices by region. The dashed lines represent the average use-to-capacity ratio (UCR) across regions for each device group. A data point positioned above the dashed line indicates that the corresponding region has a higher UCR than the regional average does, whereas a point below the line indicates lower-than-average utilization

interpreted as evidence of a fully homogeneous distribution of MDIT across the country in all respects.

In terms of capacity, the Western Black Sea region appears to cluster with the southwestern, central and central eastern Anatolian regions, whereas the western and northwestern regions are notably grouped with the Eastern Black Sea. Similarly, the central, eastern, and southeastern Anatolian regions also form a distinct cluster. However, this spatial distribution is not consistent across all analyses and varies according to device technology. Notably, for MRI and CT devices, while capacity-based clustering (Analysis 3) reveals three groups, usage-based clustering expands to five groups. This variation suggests that regional differences in capacity do not always align with patterns of usage. Moreover, when analyzing all devices collectively or focusing specifically on low-tech equipment, the composition of regional clusters shifts depending on whether capacity or usage is considered—some regions move between clusters. These findings collectively point to a partial imbalance between capacity and actual utilization across regions.

Figure 9 provides valuable insights into regional variations in use-to-capacity ratios across different medical imaging technologies. The figure displays use-to-capacity ratios for high-tech and low-tech devices, represented by orange and blue shaded areas, respectively. For each device group, the ratio was calculated by first applying min–max normalization to both usage and capacity values for individual devices. Then, the normalized usage was divided by the normalized capacity, and the average of these values was computed across all devices within the group. The dashed lines in the figure indicate the average use-to-capacity ratio (UCR) across all regions for each respective device group. A data point positioned above the dashed line suggests that the corresponding region exhibits a higher UCR for that device group than the overall regional average does, whereas a point below the line implies lower-than-average utilization. Importantly, a low UCR may reflect underutilization of available technological capacity or overprovisioning, whereas a high ratio may point to excess demand, potential strain on resources, or inefficiencies in service delivery for that technology.

The figure enhances the understanding of the divergence between clusters formed on the basis of capacity and those formed on the basis of utilization. A key observation is the variation in use-to-capacity ratios across regions when analyzed by high-tech versus low-tech device groups. These differences help explain why certain regions tend to cluster differently depending on the metric employed. In some cases, a region's UCR for one technology group may be significantly above the average, whereas it may remain well below average for the other group.

For the high-tech group, several regions—such as Istanbul, Eastern Marmara, the Western Black Sea, and Central Anatolia—exhibit use-to-capacity ratios above the group average, suggesting relatively intensive utilization of available resources in these areas. In contrast, regions such as the Mediterranean, Western Anatolia, and Western Marmara fall significantly below the average, indicating potential underutilization or overcapacity of high-tech imaging devices. In the low-tech group, regions such as Central Eastern Anatolia, Southeastern Anatolia, Eastern Marmara, and the Western Black Sea report markedly higher ratios than the group average does, possibly reflecting elevated demand or more efficient usage of these technologies. Conversely, regions such as the Eastern Black Sea, Istanbul, and Central Anatolia demonstrate below-average utilization, which may point to inefficiencies or limitations in service delivery.

Overall, the variation in use-to-capacity ratios across regions and device groups suggests moderate imbalances in both resource allocation and utilization. Notably, some regions—e.g., Central Eastern Anatolia and the Western Black Sea—consistently show above-average utilization for both high-tech and low-tech groups, whereas others—e.g., the Mediterranean and Western Marmara—consistently fall below average in both categories. This pattern underscores the need for region-specific evaluations and targeted policy interventions to optimize the distribution and use of MDIT.

To address the observed regional disparities in the utilization of MDIT, it is essential for governments and health authorities to undertake comprehensive, evidence-based investigations. A first step would involve conducting a regional needs assessment to evaluate whether the current patterns of utilization align with the health needs and demographic profiles of the populations in each region. This includes analyzing epidemiological indicators, disease prevalence, and healthcare demand. In parallel, a facility-level operational assessment should be carried out to examine the efficiency and functionality of imaging services. This would encompass factors such as equipment availability, operational hours, staff allocation, and maintenance records. Disparities in human resources, particularly the availability of trained radiologists and technicians, should also be scrutinized, as they can significantly impact service delivery capacity. Additionally, a thorough capacity and infrastructure analysis is essential for determining whether existing imaging resources align with regional healthcare needs and utilization patterns. Such an assessment can help identify areas where diagnostic devices are underutilized due to factors such as technical malfunctions, maintenance challenges, or mismatches between supply and demand. In this context, complementing quantitative analyses with qualitative interviews involving healthcare professionals, administrators, and patients can yield valuable insights into the structural and behavioral determinants influencing utilization patterns.

## Conclusion

This study provides a comprehensive analysis of the regional distribution of medical diagnostic imaging technologies (MDITs) across Türkiye, with a focus on both capacity and utilization indicators. By employing a stratified hierarchical clustering approach, we were able to capture the heterogeneity of imaging technologies and identify meaningful regional patterns that might be obscured by aggregated data analyses. Our findings reveal that while Türkiye has made substantial progress in achieving a relatively balanced distribution of MDITs, regional disparities in utilization persist, highlighting the complex interplay between investment, demand, and service delivery.

The results demonstrate that technological availability alone does not guarantee optimal use and that some regions—despite having sufficient infrastructure—experience underutilization, whereas others achieve higher-than-expected utilization relative to their capacity. This underscores the importance of moving beyond purely quantitative metrics and integrating qualitative and contextual factors—such as local health needs, demographic profiles, and healthcare workforce distribution—into policy and planning processes.

Overall, this study contributes new empirical evidence to the discourse on healthcare equity in Türkiye and offers actionable insights for health system stakeholders. By illuminating mismatches between capacity and utilization, our findings can inform more efficient and equitable allocation of diagnostic resources, ultimately supporting the broader goals of Universal Health Coverage and regional health equity.

### Limitations

In this study, the 12 NUTS regions of Türkiye were compared in terms of the distribution of medical diagnostic imaging technologies (MDITs). These regions, defined jointly by the EU and the Republic of Türkiye, were designed to exhibit as homogeneous a distribution as possible on the basis of criteria such as population size, geographical continuity, economic characteristics and development levels, socioeconomic conditions, and cultural or historical ties. While these regions are intended to reflect internal homogeneity across multiple dimensions, some variation is still likely to emerge—particularly in analyses focused on a single or narrow set of criteria or those extending beyond the original scope of regional classification.

The analysis is based on health statistics from 2013 and 2018. Although more recent data exist for the years following 2020, these data were excluded from the study because of the extraordinary and atypical conditions caused by the COVID-19 pandemic. We believe that a detailed examination of statistical yearbooks covering the pandemic period from multiple perspectives would be both important and valuable for future research.

#### Abbreviations

| | |
|---|---|
| AEG | Aegean |
| CA | Central Anatolia |
| CaU | Capacity and Use |
| CEA | Central Eastern Anatolia |
| CT | Computed Tomography |
| EBS | Eastern Black Sea |
| ECO | Echocardiography |
| EM | Eastern Marmara |
| EU | European Union |
| DUS | Doppler Ultrasonography |
| GIS | Geographic Information System |
| HR | Healthcare Resources |
| IST | Istanbul |
| MAM | Mammography |
| MDIT | Medical Diagnostic Imaging Technologies |
| MED | Mediterranean |

| | |
|---|---|
| MRI | Magnetic Resonance Imaging |
| NA | Northeastern Anatolia |
| NUTS | Nomenclature of Territorial Units for Statistics |
| PET-CT | Positron Emission Tomography-Computed Tomography |
| SA | Southeastern Anatolia |
| UHC | Universal Health Coverage |
| US | Ultrasonography |
| USI | Ultrasound Imaging |
| UCR | Use-to-Capacity Ratio |
| WA | Western Anatolia |
| WBS | Western Black Sea |
| WM | Western Marmara |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12913-025-12997-y.

Supplementary Material 1.

Supplementary Material 2.

Supplementary Material 3.

Supplementary Material 4.

**Authors' contributions**

HT: Hakan Temiz, TK: Tuncay Kara. Conceptualization: HT, TK. Methodology: HT, TK. Data collection: HT. Formal analysis: HT, TK. Writing – original draft: HT, TK. Writing – review & editing: HT. Supervision: HT, TK. Visualization: HT. Software: HT. All authors read and approved the final version of the manuscript.

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**Data availability**

The data is taken from the publicly available Statistics yearbooks' of the Ministry of Health of the Republic of Turkiye.

## Declarations

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare no competing interests.

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