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Health Care Administration/Sağlık Hizmetleri Yönetimi

Clustering Provincial Health System Performance in Türkiye: A Dual-Method Analysis

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ABSTRACT

Purpose: Türkiye, despite extensive health reforms, continues to exhibit substantial variation in health system performance across its 81 provinces. This study aimed to classify provincial health system performance in Türkiye by integrating key indicators of infrastructure and service utilization using complementary clustering methods.

Methods: This cross-sectional study used publicly available province-level data from the Türkiye Health Statistics Yearbook 2023. Six standardized indicators were analyzed for all 81 provinces. Ward's hierarchical clustering and K-means clustering were applied to identify homogeneous groups. Additional ANOVA analyses were performed to evaluate differences between clusters. Cluster patterns were further visualized using geographic maps, principal component analysis, and radar charts.

Results: Both clustering methods identified three distinct typologies of provincial health systems. Significant between-cluster differences were observed for several indicators, particularly workforce density and bed occupancy rates. One cluster demonstrated high workforce density, bed availability and service utilization, a second exhibited consistently low value across all indicators and a third represented intermediate profiles. Agreement between the two clustering methods was substantial, supporting the robustness of the classification. Geographical visualization revealed that higher-performing clusters were predominantly concentrated in western and metropolitan regions, whereas lower-capacity clusters appeared more frequently in eastern and southeastern provinces.

Conclusions: Integrating structural and utilization indicators through dual-method clustering provides a comprehensive framework for classifying provincial health system performance in Türkiye. These typologies highlight marked intra-national disparities and can inform regionally sensitive health planning within Türkiye.

Keywords: Cluster Analysis, Health Services Accessibility, Delivery of Health Care, Health Resources, Healthcare Disparities.

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ÖZET

Amaç: Türkiye, kapsamlı sağlık reformlarına rağmen, 81 il arasında sağlık sistemi performansı açısından dikkate değer farklılıklar göstermektedir. Bu çalışmanın amacı, altyapı ve hizmet kullanımına ilişkin temel göstergeleri bütüncül bir yaklaşımla ele alarak, tamamlayıcı kümeleme yöntemleri kullanımıyla Türkiye'de iller düzeyinde sağlık sistemi performansını sınıflandırmaktır.

Yöntem: Kesitsel nitelikteki bu çalışmada, Türkiye Sağlık İstatistikleri Yıllığı 2023'ten elde edilen, il düzeyinde kamuya açık veriler kullanılmıştır. Tüm 81 il için altı standartlaştırılmış gösterge analiz edilmiştir. Homojen il gruplarının belirlenmesi amacıyla Ward'ın hiyerarşik kümeleme yöntemi ve K-ortalama (K-means) kümeleme analizi uygulanmıştır. Kümeler arasındaki farklılıkları değerlendirmek için ek ANOVA analizleri yapılmıştır. Küme örüntüleri ayrıca coğrafi haritalar, temel bileşenler analizi ve radar grafikler kullanılarak görselleştirilmiştir.

Bulgular: Her iki kümeleme yöntemi de il düzeyinde sağlık sistemlerini üç farklı tipoloji altında sınıflandırmıştır. Özellikle sağlık iş gücü yoğunluğu ve yatak doluluk oranları başta olmak üzere çeşitli göstergelerde kümeler arasında anlamlı farklılıklar saptanmıştır. Bir küme, yüksek sağlık iş gücü yoğunluğu, yatak kapasitesi ve hizmet kullanım düzeyleri ile öne çıkarken; ikinci küme tüm göstergelerde düşük değerlere sahip illerden oluşmuştur. Üçüncü küme ise ara düzey performans sergileyen illeri temsil etmiştir. İki yöntem arasındaki uyumun yüksek olması, sınıflandırmanın sağlamlığını desteklemektedir. Coğrafi görselleştirmeler, daha yüksek performans gösteren kümelerin ağırlıklı olarak Türkiye'nin batı ve metropolitan bölgelerinde yoğunlaştığını, daha düşük kapasiteye sahip kümelerin ise doğu ve güneydoğu illerinde daha sık görüldüğünü ortaya koymuştur.

Sonuç: Altyapı ve hizmet kullanım göstergelerinin birlikte ele alındığı çift yöntemli kümeleme yaklaşımı, Türkiye'de il düzeyinde sağlık sistemi performansını sınıflandırmak için kapsamlı bir çerçeve sunmaktadır. Elde edilen tipolojiler, ülke içindeki belirgin bölgesel eşitsizlikleri ortaya koymakta ve bölgesel özellikleri dikkate alan sağlık planlaması ve politika geliştirme süreçlerine katkı sağlayabilecek niteliktedir.

Anahtar Kelimeler: Küme Analizi, Sağlık Hizmetlerinin Ulaşılabilirliği, Sağlık Hizmetlerinin Ulaştırılması, Sağlık Kaynakları, Sağlık Hizmeti Farklılıkları

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Ensuring equitable access to healthcare services across geographical regions remains a critical challenge for health systems worldwide. Subnational disparities in healthcare infrastructure and service utilization can hinder efficiency, quality, and equity of care delivery, particularly in countries with heterogeneous population distributions and uneven resource allocation (1). In response, health system researchers and policymakers have increasingly turned to data-driven approaches to identify regional patterns and inform targeted interventions.

Cluster analysis aims to group objects into clusters such that those within a cluster are more similar to each other than to those in other clusters (2). It has emerged as a powerful statistical method in public health for grouping geographical units based on shared characteristics. It has been widely used to detect spatial inequalities in health system performance, resource distribution, disease prevalence, and risk profiles. For example, a recent study by He et al. applied hierarchical clustering to categorize Chinese provinces based on health service capacity and socioeconomic indicators, identifying distinct typologies that inform regional health development strategies (3). Similarly, Maugeri et al. used hierarchical clustering to analyze regional differences in COVID-19 trends across Italy (4). In the Turkish context, Delil et al. conducted cluster analysis on patient mobility to examine healthcare access variations across provinces (5). While infrastructure and utilization metrics are often analyzed independently, their joint consideration offers a more complete understanding of health system functionality (6). However, few studies have integrated both healthcare infrastructure and utilization indicators to create a comprehensive typology of provincial health systems.

Türkiye's healthcare system has undergone extensive reform over the past two decades, resulting in expanded access, improved coverage, and enhanced service delivery. Nonetheless, regional disparities persist, especially in hospital bed availability, health workforce distribution, and outpatient care utilization (7). Recognizing these differences is essential for achieving policy goals related to efficiency, equity, and population health outcomes. A systematic, province-level classification of the health system could guide more equitable investment and service planning.

This study aims to construct a data-driven typology of provincial health system performance in Türkiye using six key indicators: hospital bed density, physician density, nurse density, outpatient visits per capita, average length of hospital stay, and bed occupancy rate. We employ both Ward's hierarchical clustering and K-means clustering to classify all 81 provinces into homogeneous groups, thereby providing a robust comparison of clustering methodologies. Our objectives are threefold: (1) to explore the underlying structural and operational differences among provinces, (2) to assess the agreement and complementarity of different clustering techniques, and (3) to provide policy-relevant insights that may guide regionally sensitive health system reforms.

By combining rigorous multivariate statistical methods with visual tools such as radar plots and principal component analysis (PCA), this study offers a novel approach for profiling subnational health systems and supports data-informed, geographically tailored policy development.

Material and Methods

Data Source and Study Setting

This study utilizes publicly available data from the Türkiye Health Statistics Yearbook 2023, published by the Ministry of Health (8). The dataset comprises province-level indicators for all 81 provinces in Türkiye, reflecting the status of health infrastructure and service utilization.

Variable Selection

Six key indicators were selected to represent both structural capacity and service utilization dimensions of provincial health systems:

1. Hospital bed density (beds per 10,000 population)
2. Physician density (physicians per 10,000 population)
3. Nurse density (nurses per 10,000 population)
4. Outpatient visits per capita
5. Average length of hospital stays (in days)
6. Bed occupancy rate (%)

These six variables were selected to reflect both the structural capacity and operational performance of provincial health systems. Hospital bed density, physician density, and nurse density were chosen as indicators of health infrastructure due to their widespread use in performance metrics and direct relevance to service capacity. Outpatient visits per capita, average length of hospital stay, and bed occupancy rate were included to capture service utilization and operational efficiency. These indicators are routinely used in international benchmarking studies by organizations such as the World Health Organization (WHO) and the Organization for Economic Co-operation and Development (OECD) and were selected based on both their policy relevance and complete data availability across all 81 provinces. (9, 10). Including both infrastructure and utilization measures allows for a more comprehensive and multidimensional typology of provincial health systems, as suggested by Kruk et al (6).

Data Processing

Prior to the clustering analysis, all variables were standardized using z-scores to ensure comparability and eliminate scale effects. Descriptive statistics and correlation analyses were performed to check for multicollinearity and distributional properties. No variables were excluded, and no missing data were encountered.

To identify patterns among provinces, two unsupervised learning techniques were employed:

1. Ward's Hierarchical Clustering

Agglomerative hierarchical clustering using Ward's minimum variance method was applied based on squared Euclidean distances. The optimal number of clusters was determined by examining the dendrogram and using the Elbow method to minimize within-cluster variance. This method enables hierarchical interpretation of regional similarities.

2. K-Means Clustering

To complement the hierarchical approach, K-means clustering was performed with the same number of clusters identified in the Ward method. The number of clusters (k=3) was chosen based on both the Elbow method and Silhouette score, which indicated optimal compactness and separation at this level. The algorithm was initialized with 25 random starts to ensure solution stability. K-means offers a non-hierarchical, centroid-based classification that enhances comparability.

3. Additional Statistical Analyses

To further evaluate the discriminatory validity of the identified clusters, one-way analysis of variance (ANOVA) was performed separately for both K-means and Ward cluster classifications. Differences across clusters were assessed for all six health system indicators. Effect sizes were estimated using eta-squared (η^2) to assess the magnitude of between-cluster differences. Assumptions of normality and homogeneity of variances were assessed prior to ANOVA analyses. Statistical significance was defined as $p<0.05$.

Visualization and Interpretation

All data preprocessing, clustering analyses, and visualizations were performed using Python (v3.11). The *pandas* and *numpy* libraries were used for data handling and numerical operations. Standardization of variables was conducted using *StandardScaler* from the *scikit-learn* package. Ward's hierarchical clustering was implemented via *AgglomerativeClustering*, and K-means clustering was applied using the *KMeans* class, both from *scikit-learn*. Visualizations, including dendrograms, cluster profiles, radar charts, and PCA-based scatter plots, were generated using *matplotlib, seaborn, and plotly*. Tabular outputs and formatted reports were prepared using *openpyxl* and *python-docx*.

Geographic distributions of provincial clusters were visualized using province-level administrative boundary maps of Türkiye. Cluster assignments from both K-means and Ward hierarchical clustering were integrated with publicly available provincial shapefiles using ArcGIS-based mapping tools.

Ethical Considerations

This study used publicly available, aggregate-level data from the Turkish Ministry of Health's Statistical Yearbook (2023). No individual-level or identifiable data were used. As such, ethical approval was not required in accordance with national and international research guidelines.

Results

K-means clustering identified three distinct provincial health system profiles (**Table 1**). Significant differences were observed between clusters for hospital bed density, average length of stay, bed occupancy rate, physician density, and nurse/midwife density (all $p<0.001$). The largest effect sizes were observed for nurse/midwife density ($\eta^2=0.483$) and bed occupancy rate ($\eta^2=0.414$). Outpatient visits per capita did not significantly differ across clusters ($p=0.636$).

Cluster 2 demonstrated the highest healthcare workforce and infrastructure capacity, particularly in nurse/midwife density (550.75±47.15 per 100,000 population) and hospital bed density (29.64±4.06). In contrast, Cluster 3 exhibited the lowest physician density (205.38±50.30 per 100,000 population) and bed occupancy rate (63.16±6.16%). Cluster 1 showed intermediate values across most indicators.

Ward's hierarchical clustering similarly identified three provincial groups (**Table 2**). Significant between-cluster differences were observed for bed occupancy rate, physician density, and nurse/midwife density (all $p<0.001$), whereas hospital bed density, outpatient visits per capita, and average length of stay were not significantly different. Nurse/midwife density ($\eta^2=0.554$) demonstrated the largest effect size among Ward clusters.

Table 3 presents the concordance between K-means and Ward clustering assignments. Most provinces in Ward Cluster A corresponded to K-means Cluster 2 (n=19), while Ward Cluster B aligned predominantly with K-means Cluster 3 (n=18). Provinces in Ward Cluster C were primarily classified under K-means Cluster 1 (n=21), indicating substantial agreement between the two clustering approaches.

Table 1. Cluster Means – K-means Clustering

Variables	Cluster 1 Mean ± SD	Cluster 2 Mean ± SD	Cluster 3 Mean ± SD	F	p-value	η^2
Hospital Bed Density (%)	25.75 ± 4.90	29.64 ± 4.06	22.69 ± 4.19	14.96	**<0.001**	0.277
Outpatient Visits per Capita	5.88 ± 0.87	6.11 ± 0.83	5.97 ± 0.91	0.46	0.636	0.012
Average Length of Stay (days)	5.68 ± 0.86	4.69 ± 0.80	5.08 ± 1.05	8.48	**<0.001**	0.179
Bed Occupancy Rate (%)	76.84 ± 5.93	71.53 ± 8.68	63.16 ± 6.16	27.48	**<0.001**	0.414
Physicians Density (per 100k)	279.48 ± 45.64	255.55 ± 54.56	205.38 ± 50.30	15.73	**<0.001**	0.288
Nurses/midwives Density (per 100k)	382.42 ± 100.85	550.75 ± 47.15	372.28 ± 85.18	36.46	**<0.001**	0.483

Note: Bonferroni post-hoc analyses demonstrated significant differences between Cluster 1–2, Cluster 1–3, and Cluster 2–3 for hospital bed density and bed occupancy rate; between Cluster 1–3 and Cluster 2–3 for physician density; between Cluster 1–2 and Cluster 2–3 for nurse/midwife density; and between Cluster 1–2 for average length of stay.

Table 2. Cluster Means – Ward's Hierarchical Clustering

Variables	Cluster A Mean ± SD	Cluster B Mean ± SD	Cluster C Mean ± SD	F	p-value	η^2
Hospital Bed Density (%)	26.24 ± 5.16	24.98 ± 5.27	26.55 ± 5.16	0.63	0.536	0.016
Outpatient Visits per Capita	6.08 ± 0.87	5.65 ± 0.91	6.17 ± 0.75	2.61	0.080	0.063
Average Length of Stay (days)	5.05 ± 1.06	5.13 ± 0.97	5.48 ± 0.88	1.37	0.261	0.034
Bed Occupancy Rate (%)	72.31 ± 8.08	62.50 ± 5.67	77.85 ± 5.21	33.72	**<0.001**	0.464
Physicians Density (per 100k)	278.56 ± 47.19	202.57 ± 46.10	256.53 ± 55.16	18.85	**<0.001**	0.326
Nurses/midwives Density (per 100k)	527.70 ± 67.07	395.59 ± 92.38	327.28 ± 68.96	48.44	**<0.001**	0.554

Note: Bonferroni post-hoc analyses demonstrated significant differences between all cluster pairs (A–B, A–C, and B–C) for bed occupancy rate and nurse/midwife density, whereas physician density significantly differed between Cluster A–B and Cluster B–C.

Table 3. Cluster Concordance Between Ward and K-means

Clusters	K-means Cluster 1	K-means Cluster 2	K-means Cluster 3
Ward's Cluster A	10	19	4
Ward's Cluster B	1	5	18
Ward's Cluster C	21	0	3

Figure 1 illustrates the geographic distribution of provincial clusters according to both clustering methods. Higher-capacity clusters were predominantly concentrated in western and metropolitan regions of Türkiye, whereas lower-capacity clusters appeared more frequently in eastern and southeastern provinces.

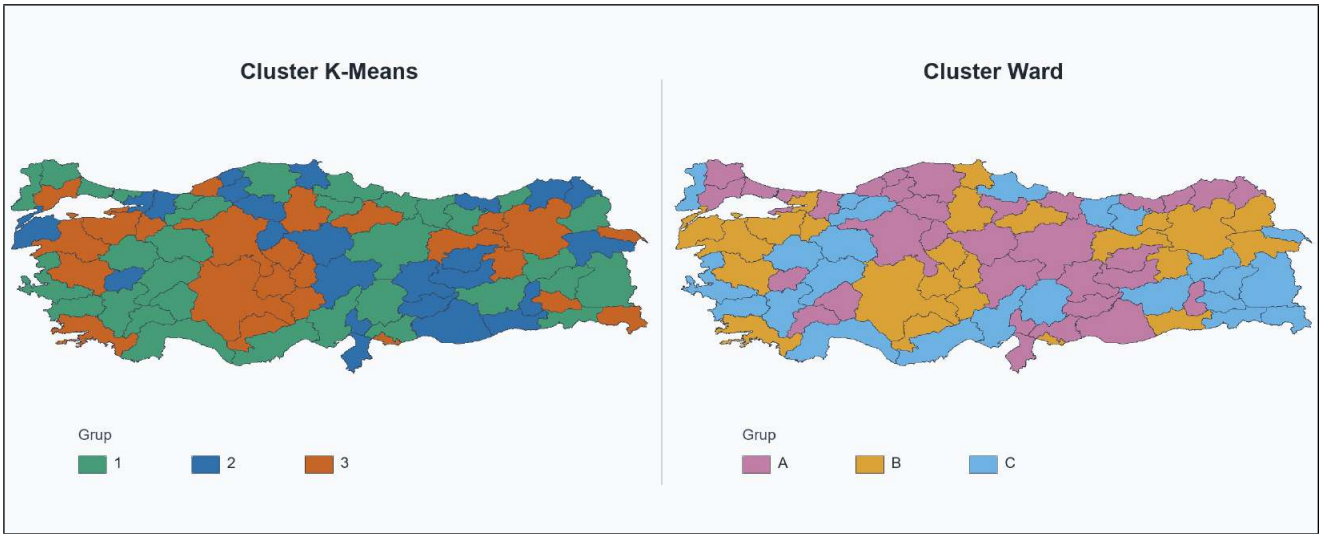

Figure 1. Türkiye maps by clustering groups.

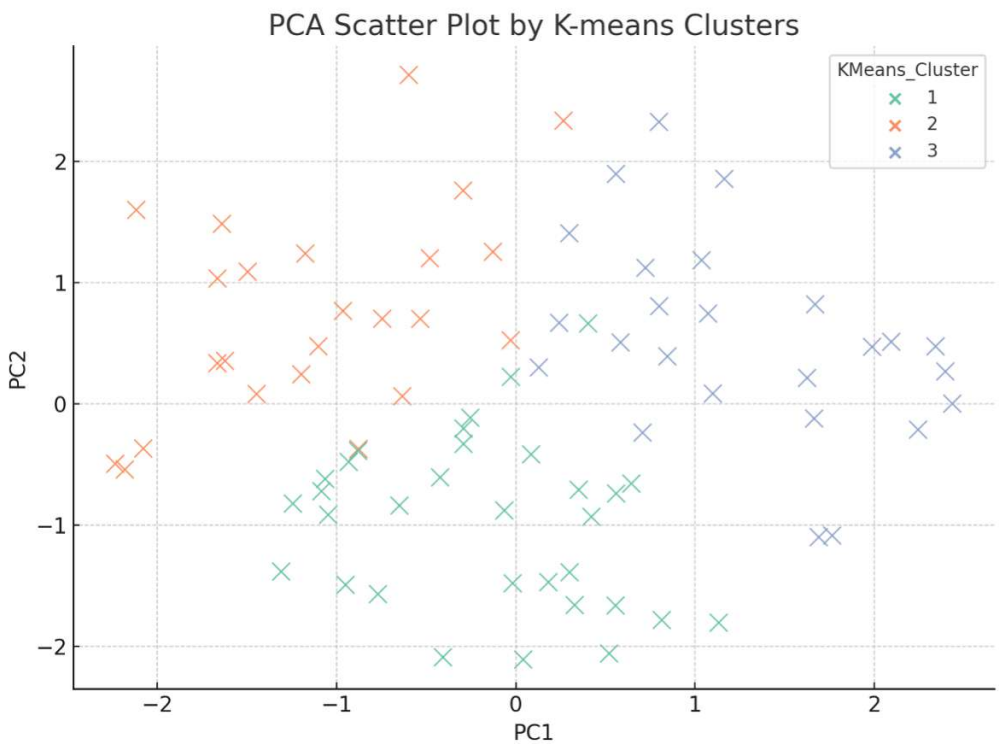

Figure 2. PCA scatter plot of provinces by K-means clusters.

Principal Component Analysis (PCA) was applied to visualize clustering patterns in reduced dimensions. The first two principal components explained 68.4% of the total variance, and the PCA scatter plot demonstrated clear separation between K-means clusters (**Figure 2**). PC1 was mainly associated with healthcare utilization indicators, whereas PC2 reflected structural healthcare capacity indicators.

Cluster profiles were further visualized using radar charts based on standardized z-score values (**Figure 3**), highlighting distinct multivariate patterns across healthcare infrastructure and utilization indicators.

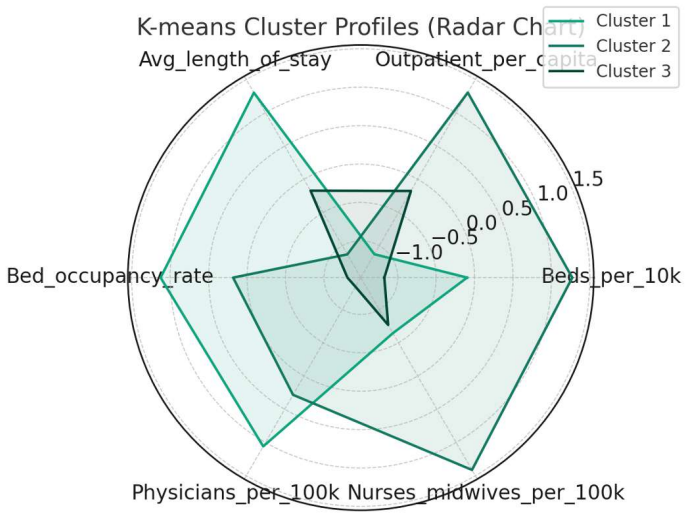

Figure 3. Radar chart of standardized indicators by K-means clusters.

Discussion

This study identified distinct provincial health system typologies in Türkiye by integrating healthcare infrastructure and service utilization indicators using both Ward's hierarchical clustering and K-means clustering methods. Additional statistical analyses demonstrated significant between-cluster differences for several indicators, particularly physician density, nurse/midwife density, and bed occupancy rates, supporting the discriminatory validity of the clustering structure. The substantial concordance observed between the two clustering approaches further reinforces the robustness of the identified provincial profiles.

Clustering techniques have increasingly been applied across diverse areas of health research, ranging from environmental health and chronic disease epidemiology to healthcare system evaluation. Chaparinia et al. used both K-means and hierarchical clustering to investigate spatial patterns of climate-related water resource indices across Iranian provinces (11). Similarly, Min et al. classified individuals with abnormal glucose metabolism into different cardiovascular risk groups using clustering analysis based on atherogenic profiles (12). In the field of healthcare systems, Kiely et al. identified distinct typologies of trans-specific healthcare systems across European countries using hierarchical and K-means clustering approaches (13). These studies demonstrate the growing utility of unsupervised learning methods for identifying latent structures within multidimensional health-related datasets.

Previous studies evaluating regional health system inequalities have often relied on a single clustering technique. Maryani et al. used K-means clustering to

classify Indonesian provinces according to maternal and child health indicators (14), whereas Yıldız applied Ward's hierarchical clustering to evaluate health service indicators across Turkish provinces (15). In contrast, the present study employed both hierarchical and centroid-based clustering methods within the same analytical framework. Although the two methods demonstrated substantial concordance, the additional ANOVA analyses suggested that they captured partially different dimensions of provincial health system performance. K-means clustering produced broader separation across infrastructure-related indicators, whereas Ward's hierarchical clustering appeared to differentiate provinces primarily according to workforce density and bed occupancy characteristics. This complementary behavior highlights the value of combining multiple unsupervised learning approaches in health systems research.

The three clusters identified in this study reflected meaningful differences in healthcare capacity and utilization patterns across provinces. Provinces within higher-capacity clusters demonstrated stronger workforce density, higher hospital bed availability, and greater bed occupancy rates, whereas lower-capacity clusters were characterized by comparatively limited healthcare resources. Interestingly, outpatient visits per capita did not significantly differ across K-means clusters. This finding may reflect the relatively standardized access to outpatient healthcare services achieved under Türkiye's universal healthcare system and nationwide primary care reforms (7, 16).

The geographic distribution of clusters revealed clear regional patterns rather than random spatial variation. Higher-capacity clusters were predominantly concentrated in western and metropolitan provinces, whereas lower-performing clusters appeared more frequently in eastern and southeastern regions. These findings are consistent with previous studies conducted in Türkiye. Bulut reported substantial east–west disparities in healthcare resilience and service delivery capacity using clustering and principal component analyses (17). Similarly, Şimşek identified pronounced spatial inequalities in healthcare workforce distribution favoring western provinces through density-based clustering analysis (18). International evidence also supports these observations; for example, studies from Indonesia and Spain have demonstrated that healthcare infrastructure and advanced medical resources tend to cluster in more urbanized and socioeconomically developed regions (14,19).

The regional disparities identified in this study likely reflect broader socioeconomic inequalities across provinces. Previous research from Türkiye has demonstrated that healthcare access and health outcomes are strongly associated with education, income, and regional development levels (20,21). The concentration of higher-performing clusters within western provinces may therefore reflect not only stronger healthcare infrastructure, but also broader socioeconomic advantages, including urbanization, higher public investment, and greater healthcare workforce availability. Conversely, lower-performing clusters in eastern and southeastern regions may be influenced by persistent structural disadvantages. Future studies integrating socioeconomic indicators such as income distribution, education level, or regional development indices may provide a more comprehensive understanding of the determinants underlying provincial health system typologies.

To improve interpretability, this study combined Principal Component Analysis (PCA), radar charts, and geographic visualization techniques. PCA facilitated dimensional reduction and enabled clearer visualization of cluster separation, whereas radar charts summarized multidimensional cluster profiles in an interpretable format. Geographic mapping further strengthened interpretation by illustrating the spatial organization of provincial health system typologies across Türkiye. Together, these visualization approaches enhanced the practical interpretability of the clustering results and supported their potential utility for evidence-informed regional health planning.

The lengthy methodological discussion regarding radar chart applications in unrelated healthcare payment reform settings can be shortened considerably, as it does not directly contribute to interpretation of the present findings.

From a policy perspective, the identified cluster typologies may support more regionally tailored healthcare planning strategies. Provinces within lower-capacity clusters may benefit from targeted investments in healthcare workforce distribution, hospital infrastructure, and service accessibility. Conversely, provinces within higher-utilization clusters may require policies focusing on efficiency optimization and sustainable resource allocation. These findings suggest that province-level typologies may provide a more informative framework for health system planning than national averages alone.

Despite the methodological rigor and nationwide scope of this study, several limitations must be acknowledged. First, the analysis is based solely on publicly available aggregated indicators, which may not capture nuances such as quality of care, unmet need, or population-level health outcomes. Second, the selection of indicators was constrained by data availability and comparability across provinces, potentially overlooking other dimensions of health system performance. Third, although we employed two clustering techniques and multiple visualization tools to enhance robustness, cluster assignment is still sensitive to algorithm-specific assumptions and parameter settings. Additionally, the cross-sectional nature of the data limits our ability to infer causal relationships or track temporal shifts in provincial health system performance. Lastly, while our findings provide useful typologies, they may oversimplify the complexity of health service delivery, particularly in provinces with heterogeneous sub-regional characteristics. Future research incorporating time-series data, qualitative inputs, and outcome-based indicators would offer a more comprehensive understanding of subnational health system dynamics in Türkiye.

Conclusion

This study provides a comprehensive classification of provincial health systems in Türkiye by integrating structural capacity and service utilization indicators through unsupervised learning methods. The identification of three distinct clusters, supported by additional statistical analyses and geographic visualization, reveals substantial intra-national heterogeneity and underscores the need for regionally differentiated health policies. By combining K-means and hierarchical clustering and enriching the analysis with principal component and radar chart visualizations, we offer a robust and interpretable framework for assessing health system performance. These typologies not only reflect existing disparities but also serve as an empirical basis for targeted resource allocation and policy interventions. As Türkiye continues to pursue health system reform and equity, data-driven tools such as clustering and multidimensional visualization can enhance strategic planning and improve responsiveness to local needs.

Declarations

Ethics approval and consent to participate

This study used publicly available, aggregate-level data from the Türkiye Health Statistics Yearbook 2023 published by the Ministry of Health. No individual-level or identifiable information was used; therefore, ethical approval and informed consent were not required in accordance with national and international research guidelines.

Conflict of interest

The authors declare no conflicts of interest related to this study.

Availability of data and material

The dataset used in this study is publicly accessible via the Türkiye Health Statistics Yearbook 2023 (https://dosyasb.saglik.gov.tr/Eklenti/50208/0/siy2023ingilizce31012025pdf.pdf), published by the Ministry of Health of the Republic of Türkiye.

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Authors' contributions

FAE was the principal investigator and was responsible for study conception, data analysis, visualization, and manuscript drafting. CB supervised the study, provided critical feedback on the methodology and interpretation, and contributed to manuscript revision. Both authors read and approved the final version of the manuscript.

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