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A MULTI-CRITERIA EVALUATION OF PROVINCIAL HEALTHCARE SERVICES IN TÜRKİYE WITH ENTROPY-SWARA-COPRAS METHOD

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ABSTRACT

This study presents an integrated multi-criteria decision-making approach to assess the healthcare performance of provinces in Turkey using official statistics from the year 2021. The evaluation is based on five key indicators related to healthcare service capacity: number of hospitals, specialist physicians, nurses, pharmacists, and general practitioners. To enhance comparability across provinces with different population sizes, all healthcare indicators were adjusted on a per capita basis. In the first stage of the analysis, objective weights were determined using the ENTROPY method, which quantifies the informational diversity of each criterion. In parallel, subjective weights were obtained through the SWARA method based on the structured evaluations of multiple decision-makers. The final weight of each indicator was calculated by integrating these objective and subjective components to reflect both statistical variation and expert judgment. Following the weighting process, the COPRAS method was applied to rank the provinces according to their overall performance in healthcare capacity. The analysis revealed considerable regional disparities, with Bayburt emerging as the top-performing province, while Istanbul ranked lowest. The proposed integrated decision model offers a systematic and replicable framework for evaluating regional healthcare infrastructure and can support more balanced resource allocation and planning at the national level.

Keywords: Multiple Criteria Decision Making, Regional Healthcare, Hybrid Criteria Weighting

JEL Classification: C44, R15

1. INTRODUCTION

Healthcare services are fundamental systems designed to protect public health, prevent diseases, provide treatment, and support rehabilitation. These services are delivered through a wide range of institutions, including hospitals, clinics, health centers, and rehabilitation units, all playing a central role in addressing the health needs of the population. A comprehensive healthcare system involves not only curative practices but also preventive and rehabilitative services, forming a multidimensional structure (Öztürk & Meral, 2016). The interaction between patients, healthcare personnel, and institutions defines the dynamic nature of healthcare provision.

One of the key elements influencing the performance of healthcare systems is the fair and efficient distribution of healthcare personnel across regions. Inadequate or uneven allocation of physicians, nurses, pharmacists, and other staff significantly impacts service quality and accessibility (Kalanlar, 2018). Therefore, the geographical distribution and professional qualifications of healthcare workers are essential factors in achieving equitable service delivery.

Healthcare services are typically divided into preventive, curative, and rehabilitative components, each with specific operational needs and resource dependencies (Sayım, 2017). Socioeconomic developments, lifestyle changes, and increasing demand for medical technology have placed additional pressure on healthcare systems, highlighting the need for efficient resource utilization (Pekkaya & Dökmen, 2019). As a result, performance evaluation has become a strategic priority in healthcare planning.

Multi-Criteria Decision-Making (MCDM) techniques have gained prominence for addressing complex assessment problems in healthcare. These methods enable systematic evaluation by considering multiple, often conflicting, criteria (Chakraborty et al., 2023). This study applies an MCDM-based approach to evaluate the healthcare performance of all 81 provinces in Türkiye, based on 2021 data and five key indicators: number of hospitals, specialist doctors, nurses, pharmacists, and general practitioners.

The evaluation was carried out using a hybrid methodology combining ENTROPY, SWARA, and COPRAS methods. The ENTROPY method was used to compute objective weights based on data variability, while the SWARA method incorporated expert judgments to determine subjective weights. These were integrated to derive composite criterion weights, which were then applied in the COPRAS method for final provincial ranking.

Importantly, population-adjusted data was used, specifically applying a transformation based on the number of people per healthcare unit. This adjustment provides a clearer picture of accessibility and ensures comparability between provinces.

The integration of quantitative data with expert evaluations enhances analytical robustness and policy relevance. By identifying disparities and prioritizing regions with lower performance, the study offers practical insights for improving healthcare resource allocation. The next sections provide a literature review, methodological explanation, and empirical findings supported by comparative analysis.

2. LITERATURE REVIEW

Multi-Criteria Decision-Making (MCDM) methods are increasingly employed in healthcare studies to enhance the effectiveness and reliability of decision-making processes. In this study, the selected methods—ENTROPY, SWARA, and COPRAS—were examined in detail through a comprehensive review of relevant academic literature. This section aims to explore the methodological characteristics of each approach and to compare how these methods have been utilized across various sectors. In doing so, the integration logic adopted in the current study is clarified and positioned within the broader context of the literature.

2.1. Studies Employing MCDM Methods

The selected MCDM methods have been widely applied in various domains, either independently or through hybrid structures. Their methodological flexibility enables tailored integration depending on the decision-making context.

2.2. Studies Using the ENTROPY Method

The ENTROPY method, widely recognized for delivering objective weights based on data variability, is frequently utilized in problems where impartiality and statistical rigor are paramount. As outlined in Table 1, ENTROPY has often been integrated with methods such as TOPSIS, MABAC, MAUT, and AHP.

Table 1. Studies Using the ENTROPY Method

Author(s) & Year	Methods Used	Application Area	Author(s) & Year
Akbulut & Hepşen (2021)	ENTROPY, COCOSO	Financial Performance Analysis	Akbulut & Hepşen (2021)
Özaydın & Karakul (2021)	ENTROPY, MAUT, SAW, EDAS	Financial Performance Evaluation	Özaydın & Karakul (2021)
Tunca et al. (2016)	ENTROPY, MAUT	OPEC Countries Performance	Tunca et al. (2016)
Ayçin & Çakın (2019)	ENTROPY, MABAC	Innovation Performance Measurement	Ayçin & Çakın (2019)
Ulutaş (2019)	ENTROPY, MABAC	Personnel Selection	Ulutaş (2019)
Hussain & Mandal (2016)	ENTROPY, COPRAS, MOORA	Material Selection	Hussain & Mandal (2016)
Chodha et al. (2021)	ENTROPY, TOPSIS	Industrial Robot Selection	Chodha et al. (2021)
Özbek & Oğuz (2024)	ENTROPY, TOPSIS	Supplier Selection	Özbek & Oğuz (2024)
Rençber (2024)	ENTROPY, TOPSIS	Sustainability Performance Evaluation	Rençber (2024)
Hokka & Bektaş (2024)	ENTROPY, ARAS	Macroeconomic Performance Measurement	Hokka & Bektaş (2024)
Topal (2024)	ENTROPY, AHP, TOPSIS	Performance Ranking	Topal (2024)
Babacan & Ömürbek (2024)	ENTROPY, CILOS, ARAS	Crime Evaluation by Province	Babacan & Ömürbek (2024)
Şeyranlıoğlu & Kara (2024)	ENTROPY, CODAS	Stock Market Performance	Şeyranlıoğlu & Kara (2024)

Sakarya & Aksu (2020)	ENTROPY, TOPSIS	Financial Performance Assessment	Sakarya & Aksu (2020)
Yüksekyıldız (2021)	ENTROPY, EATWOS	Port Efficiency Evaluation	Yüksekyıldız (2021)

While studies like Chodha et al. (2021) and Özbek & Oğuz (2024) combine ENTROPY with TOPSIS to evaluate alternatives by comparing them to ideal and anti-ideal solutions, other studies such as Ayçin & Çakın (2019) and Ulutaş (2019) favor MABAC to enable more granular regional or categorical performance evaluations. Tunca et al. (2016) and Özaydın & Karakul (2021) use MAUT, indicating a preference for utility-based evaluation in economic contexts.

A key methodological similarity among these studies is their reliance on ENTROPY for data-driven weighting, but the ranking methods they pair it with vary based on the problem's nature—TOPSIS for ideal solution ranking, MABAC for additive comparisons, and MAUT for expected utility.

In contrast, Topal (2024) and Sakarya & Aksu (2020) employ hybrid models (e.g., ENTROPY-AHP-TOPSIS) to enrich objectivity with pairwise comparison logic. This indicates a trend toward combining quantitative data with structured judgment in complex performance evaluations. Şeyranlıoğlu & Kara (2024) and Hokka & Bektaş (2024) also exemplify such hybrid integration by coupling ENTROPY with CODAS or ARAS, showing the method's adaptability across ranking systems.

The key difference among these studies lies in their application domain: while finance, logistics, and sustainability are well represented, applications in healthcare are notably absent. Moreover, only a few studies (e.g., Rençber, 2024) explicitly address regional performance, indicating that the potential of ENTROPY for spatial healthcare analysis remains largely unexplored.

2.3. Studies Using the SWARA Method

SWARA is inherently subjective, designed to incorporate expert insight in assigning weights to decision criteria. It is often favored in contexts where expertise, policy experience, or managerial knowledge must inform decisions. Table 2 reflects SWARA's wide-ranging applications when integrated with MCDM ranking methods such as COPRAS, WASPAS, ARAS, TOPSIS, and VIKOR.

Table 2. Studies Using the SWARA Method

Author(s) & Year	Methods Used	Application Area	Author(s) & Year
Katrancı & Kundakcı (2020)	SWARA, COPRAS	Cold Storage Selection	Katrancı & Kundakcı (2020)
Türkmen & Demirel (2022)	SWARA, COPRAS	Supplier Selection	Türkmen & Demirel (2022)
Maruf (2021)	SWARA, WASPAS	E-Commerce Site Ranking	Maruf (2021)
Yurdoğlu & Kundakcı (2017)	SWARA, WASPAS	Server Selection	Yurdoğlu & Kundakcı (2017)
Ulutaş (2020)	SWARA, CODAS	Cargo Company Selection	Ulutaş (2020)
Yazgan & Agamyradova (2021)	SWARA, MAIRCA	Personnel Selection	Yazgan & Agamyradova (2021)
Abdulvahitoğlu & Kılıç (2022)	SWARA, TOPSIS	Battery Evaluation for EVs	Abdulvahitoğlu & Kılıç (2022)
Ekin & Cesur (2023)	SWARA	Risk Analysis	Ekin & Cesur (2023)
Erturgut & Ustalı (2021)	SWARA, ARAS	Transportation Performance	Erturgut & Ustalı (2021)

Derse & Yontar (2020)	SWARA, TOPSIS	Renewable Energy Source Evaluation	Derse & Yontar (2020)
Arslan (2023)	SWARA, AHP	Cable Type Selection	Arslan (2023)
Gezmişoğlu et al. (2023)	SWARA, VIKOR	Supplier Evaluation	Gezmişoğlu et al. (2023)
Garayev et al. (2023)	SWARA	Aircraft Performance Parameters	Garayev et al. (2023)

A common trend observed across studies such as Katrancı & Kundakcı (2020), Türkmen & Demirel (2022), and Nebati et al. (2023) is the integration of SWARA with COPRAS or WASPAS in supplier selection and operational strategy problems. These combinations reflect SWARA's strength in real-world business settings, where expert judgment is essential for aligning evaluation models with organizational goals.

A methodological similarity among these studies is the emphasis on hybridization. For instance, Abdulvahitoğlu & Kılıç (2022) and Arslan (2023) use SWARA-TOPSIS or SWARA-AHP, enabling subjective weighting to be paired with geometric or comparative ranking models. Studies such as Yazgan & Agamyradova (2021) and Ulutaş (2020) broaden the scope by using less-common methods like MAIRCA and CODAS, indicating that SWARA is methodologically versatile and not limited to classical MCDM frameworks.

However, these studies differ in their data dependency and problem types. Some deal with quantitative operational decisions (e.g., battery, cable, or company selection), while others, such as Ekin & Cesur (2023) and Garayev et al. (2023), address strategic or risk-related problems where data is less structured.

What sets this body of work apart is SWARA's flexibility in weighing ambiguous or soft criteria, but a key gap is visible: there is no study applying SWARA to spatial health system evaluation or public service access analysis, especially not with real administrative data as used in our research.

2.4. Studies Using the COPRAS Method

COPRAS is known for its simplicity and efficiency in ranking alternatives based on both benefit and cost criteria. Its strength lies in producing linear, interpretable outputs. As shown in Table 3, COPRAS has been applied in a wide range of sectors, including banking, energy, logistics, and hospitality.

Table 3. Studies Using the SWARA Method

Author(s) & Year	Methods Used	Application Area	Author(s) & Year
Organ & Yalçın (2016)	COPRAS	Research Assistant Performance	Organ & Yalçın (2016)
Madic et al. (2014)	COPRAS	Supplier Method Selection	Madic et al. (2014)
Aydın (2020)	COPRAS, SD	Bank Performance	Aydın (2020)
Aksoy et al. (2015)	COPRAS, AHP	Coal Company Performance	Aksoy et al. (2015)
Sarıçalı & Kundakcı (2016)	COPRAS, AHP	Hotel Selection	Sarıçalı & Kundakcı (2016)
Özbek & Erol (2016)	COPRAS, MOORA	Warehouse Location Selection	Özbek & Erol (2016)
Ömürbek et al. (2017)	COPRAS, MOOSRA	Bank Sustainability Performance	Ömürbek et al. (2017)
Ayçin & Çakın (2019)	COPRAS, MACBETH	SME Financial Evaluation	Ayçin & Çakın (2019)

Mercan & Çetin (2020)	COPRAS, VIKOR	BIST Electricity Firms Analysis	Mercan & Çetin (2020)
Ersoy (2023)	COPRAS, ARAS	EU Cost of Living	Ersoy (2023)
Doğan et al. (2017)	COPRAS-G	Heavy Vehicle Selection	Doğan et al. (2017)
Nebati (2022)	COPRAS, SWARA	Tourism Marketing Strategy Evaluation	Nebati (2022)
Uygurtürk & Soylu (2016)	COPRAS	Liquidity & Profitability	Uygurtürk & Soylu (2016)

Studies like Aksoy et al. (2015) and Sarıçalı & Kundakcı (2016) combine COPRAS with AHP to structure subjective evaluations, while others such as Ömürbek et al. (2017) and Mercan & Çetin (2020) prefer integrations with MOOSRA or VIKOR for more nuanced alternative comparisons.

Interestingly, some researchers (e.g., Aydın, 2020; Doğan et al., 2017) have either modified the COPRAS method (e.g., COPRAS-G) or used simulation-based extensions (e.g., COPRAS-SD), showcasing the method's customizability to sector-specific constraints. Studies such as Nebati (2022) are especially relevant, as they integrate SWARA and COPRAS to combine subjective and quantitative insights, albeit in the tourism domain, not healthcare.

The diversity of ranking partners (AHP, VIKOR, MOORA, ARAS) across these studies reflects the scalability and robustness of COPRAS. Yet, most studies lack complex, multi-tiered regional applications and almost none target public health systems or healthcare workforce distribution.

2.5. Studies in the Healthcare Sector

Although healthcare is increasingly recognized as a critical area for decision analysis, few studies in the reviewed literature employ MCDM techniques in a systematic, regionally comparative manner. Table 4 outlines four representative studies.

Kalanlar (2018) and Karaer & Tatlıdil (2019) provide broad sectoral analyses, including both public and private health indicators, while Pekkaya & Dökmen (2019) focus on budgetary performance of public health expenditures. Öztürk & Meral (2016) analyze hospital capacity, yet these studies largely remain descriptive and do not adopt rigorous multi-criteria frameworks.

A key methodological limitation in this subset is the lack of integrated weighting and ranking models. Unlike the financial or manufacturing domains, healthcare studies rarely combine subjective and objective perspectives, nor do they rely on formalized MCDM structures. Most importantly, these studies do not employ models that compare provincial-level healthcare systems using real personnel data, nor do they offer systematic prioritization of service adequacy or equity.

In summary, although ENTROPY, SWARA, and COPRAS have been applied effectively in various sectors, their integrated application within the healthcare domain, especially for evaluating regional health system performance, is exceptionally limited. The existing literature indicates that MCDM methods remain underutilized in assessing spatial equity, healthcare personnel distribution, and service accessibility. This study fills this critical research gap by proposing a comprehensive hybrid MCDM framework that incorporates the objectivity of ENTROPY, the contextual insight of SWARA, and the ranking capability of COPRAS, all applied to a real-world national dataset.

3. METHODOLOGY

Multi-Criteria Decision-Making (MCDM) approaches aim to evaluate alternatives based on multiple, often conflicting criteria. These methods are divided into two main groups: (i) methods for determining the importance (weights) of criteria, and (ii) methods for ranking the alternatives using these weights (Fendoğlu, 2021). Weight determination methods themselves fall into two categories:

- Objective weighting methods, which are based on statistical properties of data, and
- Subjective weighting methods, which reflect expert judgment and preferences.

This study employs a hybrid weighting framework by combining the objective ENTROPY method and the subjective SWARA method. The derived weights are integrated to form composite weights that reflect both data-driven insights and expert-based contextual knowledge. Finally, the COPRAS (Complex Proportional Assessment) method is used to rank the alternatives. The overall structure of the methodological process is also summarized in the following pseudocode to provide a clear computational flow.

```
Begin

Step 1: Objective Weight Calculation using ENTROPY
  1.1 Construct the decision matrix D (m × n) based on criteria values
  1.2 Normalize the matrix:
  1.3 Calculate entropy value for each criterion:
  1.4 Calculate degree of diversification:
  1.5 Compute objective weights:

Step 2: Subjective Weight Calculation using SWARA
  2.1 Experts rank criteria from most to least important
  2.2 For j ≥ 2, determine relative importance s_j compared to previous criterion
  2.3 Calculate coefficients:
  2.4 Calculate interim weights:
  2.5 Normalize subjective weights:

Step 3: Integration of Weights
  3.1 Combine objective and subjective weights:

Step 4: Alternative Ranking using COPRAS
  4.1 Construct normalized decision matrix E from alternatives and criteria
  4.2 Normalize the matrix:
  4.3 Calculate total benefit and cost scores:
  4.4 Calculate relative significance of alternatives:
  4.5 Normalize utility score:

Step 5: Rank alternatives based on NQ_i (descending order)

End
```

Figure 1. Pseudocode for the Proposed Hybrid MCDM Methodology

Step 1: Objective criteria weights are calculated using the ENTROPY method, which quantifies the information content of each criterion based on the diversity or variability of its values across alternatives. This method is entirely data-driven and independent of expert judgment.

Step 1.1: The decision matrix is constructed, where each row represents an alternative and each column represents a criterion. The matrix is defined as:

$$D = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ & & \ddots & \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \tag{1}$$

Here, X_{ij} denotes the performance score of the i^{th} alternative with respect to the j^{th} criterion.

Step 1.2: The decision matrix is normalized to eliminate unit-based inconsistencies. For cost-type criteria, normalization is performed as:

$$r_{ij} = \frac{\min(z_j)}{z_{ij}}, \quad \min(z_j) \neq 0 \tag{2}$$

For benefit-type criteria, normalization is carried out by dividing each value by the sum of its column:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3}$$

This transformation ensures all values fall between 0 and 1 and become dimensionless.

Step 1.3: The entropy coefficient is calculated to normalize entropy values across different numbers of alternatives:

$$k = \frac{1}{\ln(m)} \tag{4}$$

Here, m represents the number of alternatives.

Step 1.4: The entropy value for each criterion is computed using the normalized values. This value measures the uncertainty or uniformity in the distribution of criterion scores:

$$e_j = -k \sum_{i=1}^{m} r_{ij} \ln(r_{ij}) \tag{5}$$

A lower entropy indicates higher information content and variability.

Step 1.5: The degree of diversification is calculated to reflect the information richness of each criterion:

$$d_j = 1 - e_j \tag{6}$$

Criteria with greater discrimination power yield higher d_j values.

Step 1.6: Objective weights are obtained by normalizing the diversification scores, ensuring that the sum of weights equals 1:

$$w_j^E = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{7}$$

These weights represent the objective importance of each criterion based solely on data variability.

Step 2: Subjective criteria weights are calculated using the SWARA method, which incorporates expert judgment into the weighting process through pairwise importance comparisons.

Step 2.1: Criteria are ranked by experts from most to least important based on their perceived relevance to the decision problem.

Step 2.2: Starting from the second criterion, each one is compared to the previous to assess how much less important it is. This is represented as the relative importance score .

Step 2.3: A coefficient is calculated for each criterion based on the relative importance:

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{8}$$

This coefficient reflects the comparative impact of one criterion relative to the one ranked above it.

Step 2.4: A temporary weight is computed for each criterion based on the coefficients calculated in the previous step:

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{j-1}}{k_j}, & j > 1 \end{cases} \tag{9}$$

Each q_j value is recursively dependent on the weight of the previous criterion.

Step 2.5: Subjective weights are determined by normalizing the temporary weights:

$$w_j^S = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{10}$$

These weights represent the relative importance of each criterion based on expert evaluation.

Step 3: Final weights are calculated by integrating the objective and subjective weights obtained from ENTROPY and SWARA respectively. This integration allows the method to benefit from both data-driven analysis and expert opinion.

$$w_j = \lambda w_j^E + (1 - \lambda) w_j^S \tag{11}$$

Here, $\lambda \in [0,1]$ is the balance coefficient that determines the contribution of objective and subjective weights. For instance, $\lambda = 0.5$ gives equal importance to both. This combined approach reduces bias while leveraging the strengths of both perspectives.

Step 4: Alternatives are ranked using the COPRAS method, which simultaneously considers benefit and cost criteria to assess the relative performance of each alternative.

Step 4.1: A final decision matrix is constructed, containing the performance values of alternatives under each criterion:

$$E = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1n} \\ Z_{21} & Z_{22} & \cdots & Z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{m1} & Z_{m2} & \cdots & Z_{mn} \end{bmatrix} \tag{12}$$

Step 4.2: The matrix is normalized to bring values to a comparable scale:

$$d_{ij} = \frac{x_{ij} \cdot q_i}{\sum_{i=1}^{m} x_{ij}} \tag{13}$$

Step 4.3: The total benefit and cost values are calculated for each alternative. Benefit-type criteria are maximized:

$$s_i^+ = \sum_{j=1}^{n} d_{+ij} \tag{14}$$

Cost-type criteria are minimized:

$$s_i^- = \sum_{j=1}^{n} d_{-ij} \tag{15}$$

Step 4.4: The relative significance score is computed for each alternative, balancing both benefit and cost dimensions:

$$Q_i = s_i^+ + \frac{s_{min}^- \sum_{i=1}^{m} s_i^-}{s_i^- \sum_{i=1}^{m} s_{min}^-} \tag{16}$$

This allows the assessment of each alternative's overall utility.

Step 4.5: The scores are normalized to obtain relative utility values:

$$NQ_i = \left(\frac{Q_i}{Q_{max}}\right) \cdot 100 \tag{17}$$

Alternatives are then ranked in descending order of NQ_i, where the highest value indicates the most preferred option.

Numerical Application

In this study, healthcare data from all 81 provinces in Turkey were analyzed. The datasets were obtained from the Turkish Statistical Institute (TUIK). For more detailed information, refer to https://data.tuik.gov.tr. The dataset includes five variables from the year 2021: Number of Hospitals (C1), Number of Specialist Physicians (C2), Number of Nurses (C3), Number of Pharmacists (C4), and Number of General Practitioners (C5). These variables were used to conduct a performance evaluation.

In the analytical process, the first step involved calculating the objective weights of the criteria using the Entropy method. This calculation was carried out using the formula represented by Equation (1),

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and the resulting decision matrix is presented in Table 5. In this study, only the population-adjusted approach using the number of people per unit of each healthcare indicator (i.e., population divided by criterion) was applied to ensure comparability and consistency across provinces.

Table 5 presents the decision matrix used in both the Entropy and COPRAS approaches. For instance, the value for the hospital criterion in Adana indicates that approximately 70730 people are served per hospital.

Table 5. Population-Adjusted Decision Matrix for Health Indicators by Province (2021)

Province	C1	C2	C3	C4	C5	Province	C1	C2	C3	C4	C5
Adana	70730	868	372	2093	1753	Kayseri	83828	1577	522	3134	2750
Adıyaman	188614	4725	1450	9352	4920	Kilis	1131686	18552	4473	37104	11316
Afyonkarahisar	102880	3810	1065	7254	4377	Kocaeli	78047	1122	441	3251	2053
Aksaray	226337	7277	2326	12933	7595	Konya	50297	1039	315	2201	1601
Amasya	323339	9391	2650	15609	9238	Kütahya	161669	5203	1136	9840	5132
Ankara	26944	215	109	744	781	Kırklareli	226337	6466	2574	13553	8477
Antalya	49203	669	354	1519	1534	Kırıkkale	323339	7569	2540	19511	9927
Ardahan	754457	30178	9840	87052	25431	Kırşehir	377228	12368	3621	23576	12039
Artvin	282921	18552	5120	39708	13801	Malatya	119124	2520	798	6167	4191
Aydın	98407	2002	778	4191	3219	Manisa	80834	1652	608	3520	2500
Ağrı	251485	8351	2753	17821	6656	Mardin	188614	4846	1504	7595	3348
Balıkesir	90534	1983	680	3956	2733	Mersin	87052	1287	493	2560	2111
Bartın	754457	17410	4464	25148	14602	Muğla	102880	2035	941	4230	3289
Batman	188614	5453	1401	10527	5215	Muş	323339	11040	3266	26015	7997
Bayburt	2263373	33284	8705	102880	27269	Nevşehir	226337	10430	2879	16520	10335
Bilecik	282921	14989	3895	29017	13634	Niğde	282921	9391	2894	15397	9017
Bingöl	282921	14146	3224	23576	9840	Ordu	125742	3586	1157	6900	3963
Bitlis	282921	10676	2441	24601	7469	Osmaniye	226337	6796	1939	9053	6003
Bolu	205761	5672	1949	14989	9238	Rize	205761	6411	2216	15502	8573
Burdur	282921	12436	3117	17146	10014	Sakarya	125742	2641	953	5701	3445
Bursa	53889	726	288	1723	1380	Samsun	87052	1414	493	3575	2492
Denizli	98407	1900	820	4048	3644	Siirt	282921	11204	3285	21555	9238
Diyarbakır	80834	1604	500	3686	2103	Sinop	323339	15190	3558	23576	11607
Düzce	251485	6150	2613	16166	9672	Sivas	113168	3686	968	8605	4499
Edirne	205761	4294	1375	10382	7646	Tekirdağ	113168	2495	941	5644	3674
Elâzığ	174105	3323	942	9927	5179	Tokat	150891	4952	1187	9089	5574
Erzincan	226337	9200	3353	28292	11850	Trabzon	102880	2307	739	5672	3778
Erzurum	107779	3025	715	7595	3704	Tunceli	377228	32333	9550	90534	20208
Eskişehir	150891	1985	657	4877	4122	Uşak	282921	7348	2223	14325	9430
Gaziantep	68587	1267	409	2736	1900	Van	150891	3117	769	7348	3289
Giresun	125742	5894	1440	10430	6019	Yalova	323339	8638	3285	20029	11094
Gümüşhane	377228	22409	6448	51440	16052	Yozgat	141460	7420	1844	15502	6084
Hakkâri	452674	12436	4899	43526	8112	Zonguldak	188614	4183	1197	9053	5878
Hatay	94307	1729	595	3113	1755	Çanakkale	161669	3869	1353	9470	5878
Isparta	150891	3638	1164	10288	6858	Çankırı	251485	18106	5227	32802	14325
Iğdır	565843	19854	5971	37722	14508	Çorum	141460	5467	1407	10676	5715
Kahramanmaraş	119124	2746	763	5155	3238	İstanbul	9672	96	53	304	247

Karabük	377228	9163	3100	22862	10777	İzmir	35926	338	179	1004	970
Karaman	377228	11431	3476	19681	11607	Şanlıurfa	113168	2048	586	2898	1717
Kars	282921	10626	3233	31878	10430	Şırnak	323339	8260	2916	18705	5414
Kastamonu	133139	9089	2387	16166	6448	Minimum	9672.53	96.35	53.37	304.01	247.28

The decision matrix that presents the number of people per unit of each healthcare criterion is shown in Table 5. Since all criteria in the study are cost-type (i.e., lower values are more favorable), a standardization process was applied using Equation (2). In this step, the minimum value in each column (for each criterion) was divided by all the corresponding values in that column. Following the construction of the decision matrix, the standardization process was further refined using Equation (3), which is a necessary step in calculating the criterion weights via the ENTROPY method. The standardized decision matrix is provided in Table 6.

Table 6. Standardized Population-Adjusted Decision Matrix for Health Indicators by Province (2021)

Province	C1	C2	C3	C4	C5	Province	C1	C2	C3	C4	C5
Adana	0.13	0.11	0.14	0.14	0.14	Kayseri	0.11	0.06	0.10	0.09	0.08
Adıyaman	0.05	0.02	0.03	0.03	0.05	Kilis	0.00	0.00	0.01	0.00	0.02
Afyonkarahisar	0.09	0.02	0.05	0.04	0.05	Kocaeli	0.12	0.08	0.12	0.09	0.12
Aksaray	0.04	0.01	0.02	0.02	0.03	Konya	0.19	0.09	0.16	0.13	0.15
Amasya	0.02	0.01	0.02	0.01	0.02	Kütahya	0.05	0.01	0.04	0.03	0.04
Ankara	0.35	0.44	0.48	0.40	0.31	Kırklareli	0.04	0.01	0.02	0.02	0.02
Antalya	0.19	0.14	0.15	0.20	0.16	Kırıkkale	0.02	0.01	0.02	0.01	0.02
Ardahan	0.01	0.00	0.00	0.00	0.00	Kırşehir	0.02	0.00	0.01	0.01	0.02
Artvin	0.03	0.00	0.01	0.00	0.01	Malatya	0.08	0.03	0.06	0.04	0.05
Aydın	0.09	0.04	0.06	0.07	0.07	Manisa	0.11	0.05	0.08	0.08	0.09
Ağrı	0.03	0.01	0.01	0.01	0.03	Mardin	0.05	0.01	0.03	0.04	0.07
Balıkesir	0.10	0.04	0.07	0.07	0.09	Mersin	0.11	0.07	0.10	0.11	0.11
Bartın	0.01	0.00	0.01	0.01	0.01	Muğla	0.09	0.04	0.05	0.07	0.07
Batman	0.05	0.01	0.03	0.02	0.04	Muş	0.02	0.00	0.01	0.01	0.03
Bayburt	0.00	0.00	0.00	0.00	0.00	Nevşehir	0.04	0.00	0.01	0.01	0.02
Bilecik	0.03	0.00	0.01	0.01	0.01	Niğde	0.03	0.01	0.01	0.01	0.02
Bingöl	0.03	0.00	0.01	0.01	0.02	Ordu	0.07	0.02	0.04	0.04	0.06
Bitlis	0.03	0.00	0.02	0.01	0.03	Osmaniye	0.04	0.01	0.02	0.03	0.04
Bolu	0.04	0.01	0.02	0.02	0.02	Rize	0.04	0.01	0.02	0.01	0.02
Burdur	0.03	0.00	0.01	0.01	0.02	Sakarya	0.07	0.03	0.05	0.05	0.07
Bursa	0.17	0.13	0.18	0.17	0.17	Samsun	0.11	0.06	0.10	0.08	0.09
Denizli	0.09	0.05	0.06	0.07	0.06	Siirt	0.03	0.00	0.01	0.01	0.02
Diyarbakır	0.11	0.06	0.10	0.08	0.11	Sinop	0.02	0.00	0.01	0.01	0.02
Düzce	0.03	0.01	0.02	0.01	0.02	Sivas	0.08	0.02	0.05	0.03	0.05
Edirne	0.04	0.02	0.03	0.02	0.03	Tekirdağ	0.08	0.03	0.05	0.05	0.06
Elâzığ	0.05	0.02	0.05	0.03	0.04	Tokat	0.06	0.01	0.04	0.03	0.04
Erzincan	0.04	0.01	0.01	0.01	0.02	Trabzon	0.09	0.04	0.07	0.05	0.06
Erzurum	0.08	0.03	0.07	0.04	0.06	Tunceli	0.02	0.00	0.00	0.00	0.01
Eskişehir	0.06	0.04	0.08	0.06	0.05	Uşak	0.03	0.01	0.02	0.02	0.02
Gaziantep	0.14	0.07	0.13	0.11	0.13	Van	0.06	0.03	0.06	0.04	0.07

Giresun	0.07	0.01	0.03	0.02	0.04	Yalova	0.02	0.01	0.01	0.01	0.02
Gümüşhane	0.02	0.00	0.00	0.00	0.01	Yozgat	0.06	0.01	0.02	0.01	0.04
Hakkâri	0.02	0.00	0.01	0.00	0.03	Zonguldak	0.05	0.02	0.04	0.03	0.04
Hatay	0.10	0.05	0.08	0.09	0.14	Çanakkale	0.05	0.02	0.03	0.03	0.04
Isparta	0.06	0.02	0.04	0.02	0.03	Çankırı	0.03	0.00	0.01	0.00	0.01
Iğdır	0.01	0.00	0.00	0.00	0.01	Çorum	0.06	0.01	0.03	0.02	0.04
Kahramanmaraş	0.08	0.03	0.06	0.05	0.07	İstanbul	1	1	1	1	1
Karabük	0.02	0.01	0.01	0.01	0.02	İzmir	0.26	0.28	0.29	0.30	0.25
Karaman	0.02	0.00	0.01	0.01	0.02	Şanlıurfa	0.08	0.04	0.09	0.10	0.14
Kars	0.03	0.00	0.01	0.00	0.02	Şırnak	0.02	0.01	0.01	0.01	0.04
Kastamonu	0.07	0.01	0.02	0.01	0.03						

After the standardization process, normalization is applied using Equation (4) to transform the standardized values into comparable proportions. This normalization step is crucial in multi-criteria decision-making processes as it ensures that all criteria, regardless of their original scale or unit of measurement, are brought to a common dimension. By converting the standardized values into normalized values, the relative contribution of each criterion to the decision matrix is balanced. This prevents criteria with larger numerical scales from dominating the analysis. The resulting normalized values provide a fair and dimensionless basis for computing entropy values and ultimately determining objective weights. The normalized decision matrix is presented in Table 7.

Table 7. Normalized Decision Matrix for Population-Adjusted Health Indicators

Province	C1	C2	C3	C4	C5	Province	C1	C2	C3	C4	C5
Adana	0,02	0,02	0,02	0,02	0,02	Kayseri	0,01	0,01	0,01	0,01	0,01
Adıyaman	0,00	0,00	0,00	0,00	0,00	Kilis	0,00	0,00	0,00	0,00	0,00
Afyonkarahisar	0,01	0,00	0,00	0,00	0,00	Kocaeli	0,01	0,02	0,02	0,01	0,02
Aksaray	0,00	0,00	0,00	0,00	0,00	Konya	0,02	0,02	0,03	0,02	0,02
Amasya	0,00	0,00	0,00	0,00	0,00	Kütahya	0,00	0,00	0,00	0,00	0,00
Ankara	0,05	0,11	0,08	0,08	0,05	Kırklareli	0,00	0,00	0,00	0,00	0,00
Antalya	0,02	0,03	0,02	0,04	0,02	Kırıkkale	0,00	0,00	0,00	0,00	0,00
Ardahan	0,00	0,00	0,00	0,00	0,00	Kırşehir	0,00	0,00	0,00	0,00	0,00
Artvin	0,00	0,00	0,00	0,00	0,00	Malatya	0,01	0,00	0,01	0,00	0,01
Aydın	0,01	0,01	0,01	0,01	0,01	Manisa	0,01	0,01	0,01	0,01	0,01
Ağrı	0,00	0,00	0,00	0,00	0,00	Mardin	0,00	0,00	0,00	0,00	0,01
Balıkesir	0,01	0,01	0,01	0,01	0,01	Mersin	0,01	0,01	0,01	0,02	0,02
Bartın	0,00	0,00	0,00	0,00	0,00	Muğla	0,01	0,01	0,01	0,01	0,01
Batman	0,00	0,00	0,00	0,00	0,00	Muş	0,00	0,00	0,00	0,00	0,00
Bayburt	0,00	0,00	0,00	0,00	0,00	Nevşehir	0,00	0,00	0,00	0,00	0,00
Bilecik	0,00	0,00	0,00	0,00	0,00	Niğde	0,00	0,00	0,00	0,00	0,00
Bingöl	0,00	0,00	0,00	0,00	0,00	Ordu	0,01	0,00	0,00	0,00	0,01
Bitlis	0,00	0,00	0,00	0,00	0,00	Osmaniye	0,00	0,00	0,00	0,00	0,00
Bolu	0,00	0,00	0,00	0,00	0,00	Rize	0,00	0,00	0,00	0,00	0,00
Burdur	0,00	0,00	0,00	0,00	0,00	Sakarya	0,01	0,00	0,01	0,01	0,01
Bursa	0,02	0,03	0,03	0,03	0,03	Samsun	0,01	0,01	0,01	0,01	0,01
Denizli	0,01	0,01	0,01	0,01	0,01	Siirt	0,00	0,00	0,00	0,00	0,00
Diyarbakır	0,01	0,01	0,01	0,01	0,02	Sinop	0,00	0,00	0,00	0,00	0,00
Düzce	0,00	0,00	0,00	0,00	0,00	Sivas	0,01	0,00	0,01	0,00	0,00

Edirne	0,00	0,00	0,00	0,00	0,00	Tekirdağ	0,01	0,00	0,01	0,01	0,01
Elâzığ	0,00	0,00	0,01	0,00	0,00	Tokat	0,00	0,00	0,00	0,00	0,00
Erzincan	0,00	0,00	0,00	0,00	0,00	Trabzon	0,01	0,01	0,01	0,01	0,01
Erzurum	0,01	0,00	0,01	0,00	0,01	Tunceli	0,00	0,00	0,00	0,00	0,00
Eskişehir	0,00	0,01	0,01	0,01	0,01	Uşak	0,00	0,00	0,00	0,00	0,00
Gaziantep	0,02	0,01	0,02	0,02	0,02	Van	0,00	0,00	0,01	0,00	0,01
Giresun	0,01	0,00	0,00	0,00	0,00	Yalova	0,00	0,00	0,00	0,00	0,00
Gümüşhane	0,00	0,00	0,00	0,00	0,00	Yozgat	0,01	0,00	0,00	0,00	0,00
Hakkâri	0,00	0,00	0,00	0,00	0,00	Zonguldak	0,00	0,00	0,00	0,00	0,00
Hatay	0,01	0,01	0,01	0,01	0,02	Çanakkale	0,00	0,00	0,00	0,00	0,00
Isparta	0,00	0,00	0,00	0,00	0,00	Çankırı	0,00	0,00	0,00	0,00	0,00
Iğdır	0,00	0,00	0,00	0,00	0,00	Çorum	0,01	0,00	0,00	0,00	0,00
Kahramanmaraş	0,01	0,00	0,01	0,01	0,01	İstanbul	0,15	0,25	0,18	0,20	0,17
Karabük	0,00	0,00	0,00	0,00	0,00	İzmir	0,04	0,07	0,05	0,06	0,04
Karaman	0,00	0,00	0,00	0,00	0,00	Şanlıurfa	0,01	0,01	0,01	0,02	0,02
Kars	0,00	0,00	0,00	0,00	0,00	Şırnak	0,00	0,00	0,00	0,00	0,00
Kastamonu	0,01	0,00	0,00	0,00	0,00						

Using the normalized values presented in the previous step, entropy scores were calculated for each criterion based on Equation (5). This entropy value quantifies the amount of uncertainty or disorder within each criterion's distribution across alternatives. A lower entropy value indicates higher differentiation capability and greater information content, while a higher entropy suggests more uniform distribution and less discriminative power.

To determine the information contribution of each criterion, diversification degrees were computed using Equation (6), where each diversification score is derived by subtracting the entropy from 1. These scores represent the variation and informativeness of each indicator.

Finally, Equation (7) was applied to normalize the diversification scores and derive the objective weights of the criteria. These weights are essential for reflecting the inherent information embedded in each criterion without the influence of decision-maker bias.

The entropy values, diversification degrees, and final objective weights are presented in Table 8, which summarizes the results of the entropy-based weighting procedure.

Tablo 8. Entropy Values and Weights of Population-Adjusted Health Criteria

Province	C1	C2	C3	C4	C5
e_j	1,220	1,035	1,140	1,113	1,190
d_j	-0,220	-0,036	-0,140	-0,113	-0,190
w_j^E	0,314	0,0513	0,200	0,162	0,271

In the subsequent phase of the analysis, subjective weights of the criteria were determined using the Step-Wise Weight Assessment Ratio Analysis (SWARA) method. SWARA is a structured decision-making approach that incorporates expert judgment to assess the relative importance of each criterion. Since multiple decision-makers participated in the evaluation process, individual rankings were obtained from each expert.

To achieve a consolidated perspective, the geometric mean of the individual rankings was calculated, ensuring a balanced reflection of expert opinions and reducing the impact of any individual bias. The final subjective weights derived from this process are presented in Table 9.

Tablo 9. Importance Rankings of Criteria

Criteria	DM1	DM2	DM3	Geometric Mean
C1	1	2	1	1,26
C2	2	3	4	2,88
C3	3	1	2	1,82
C4	5	4	5	4,64
C5	4	5	3	3,91

The subjective weights of the criteria were calculated using the Step-Wise Weight Assessment Ratio Analysis (SWARA) method, following the structured mathematical steps illustrated in Equations (8) through (10). Beginning with the most important criterion, each subsequent criterion was evaluated by experts in terms of its relative importance compared to the previous one. This comparison yielded the relative importance coefficient s_j.

Using Equation (8), the coefficient k_j was calculated to reflect the comparative impact of one criterion relative to the previous criterion. Based on these coefficients, temporary weights q_j were recursively derived using Equation (9), where each weight depends on the value of the preceding one. Finally, the subjective weights w_j^S were obtained by normalizing the temporary weights using Equation (10), ensuring the sum of all weights equals one.

These calculations allow for expert-driven prioritization of the criteria and are summarized in Table 10, which presents the final subjective weights assigned to each criterion.

Tablo 10. Subjective Weights of Health Criteria Derived from the SWARA Method

DM1						
Criteria	**Importance Order**	**Criteria Order**	s_j	k_j	q_j	w_j^S
C1	1,26	1		1	1,00	0,23
C3	1,82	2	0,05	1,05	0,95	0,22
C2	2,88	3	0,10	1,10	0,87	0,20
C5	3,91	4	0,10	1,10	0,79	0,18
C4	4,64	5	0,20	1,20	0,66	0,15
DM2						
Criteria	**Importance Order**	**Criteria Order**	s_j	k_j	q_j	w_j^S
C1	1,26	1		1	1,00	0,24
C3	1,82	2	0,05	1,05	0,95	0,23
C2	2,88	3	0,15	1,15	0,83	0,20
C5	3,91	4	0,15	1,15	0,72	0,17
C4	4,64	5	0,10	1,10	0,65	0,16

DM3						
Criteria	Importance Order	Criteria Order	s_j	k_j	q_j	w_j^S
C1	1,26	1		1	1,00	0,24
C3	1,82	2	0,10	1,10	0,91	0,21
C2	2,88	3	0,05	1,05	0,87	0,20
C5	3,91	4	0,10	1,10	0,79	0,19
C5	4,64	5	0,15	1,15	0,68	0,16

The subjective weights of the criteria were determined using the SWARA method based on expert evaluations from three decision-makers. Each expert provided a ranking of the five criteria, which were then processed through SWARA steps using Equations (8), (9), and (10). After obtaining individual weights for each expert, the geometric mean was used to aggregate these values, ensuring a balanced and representative final subjective weighting.

The resulting subjective weights, rounded to three decimal places, are as follows:

- C1 (Number of Hospitals): 0.237
- C3 (Number of Nurses): 0.222
- C2 (Number of Specialist Physicians): 0.202
- C5 (Number of General Practitioners): 0.181
- C4 (Number of Pharmacists): 0.158

These values indicate that C1 was considered the most important criterion by the decision-makers, while C4 was perceived as the least important. The subjective weighting process adds an expert-informed perspective to the overall evaluation, which complements the objective weightings derived from the entropy method.

Below are the subjective weights obtained from the SWARA method, the objective weights calculated using the ENTROPY method, and the final integrated weights derived by equally combining both sources of information (λ = 0.5). These integrated weights were later used in the COPRAS-based evaluation of the alternatives.

Table 11. Integrated Weights of Population-Adjusted Health Criteria Based on ENTROPY and SWARA Methods

Province	C1	C2	C3	C4	C5
w_j^S	0.237	0.202	0.222	0.158	0.181
w_j^E	0.314	0.051	0.201	0.162	0.272
w_j	0.275	0.127	0.211	0.160	0.226

Equal importance was given to both subjective and objective sources by setting λ = 0.5 during the integration.

The numerical analysis continues by multiplying the normalized values presented in Table 7 with the integrated weights obtained in Table 11. This operation yields the weighted normalized decision matrix, which reflects the relative performance of each province based on population-adjusted healthcare indicators. The results of this multiplication are presented in Table 12.

Table 12. Weighted Normalized Values for Population-Adjusted Health Indicators

Province	C1	C2	C3	C4	C5	Province	C1	C2	C3	C4	C5
Adana	3.9E-06	1.5E-04	5.7E-04	7.6E-05	1.3E-04	Kayseri	3.3E-06	8.0E-05	4.0E-04	5.1E-05	8.2E-05
Adıyaman	1.5E-06	2.7E-05	1.5E-04	1.7E-05	4.6E-05	Kilis	2.4E-07	6.8E-06	4.7E-05	4.3E-06	2.0E-05
Afyonkarahisar	2.7E-06	3.3E-05	2.0E-04	2.2E-05	5.2E-05	Kocaeli	3.5E-06	1.1E-04	4.8E-04	4.9E-05	1.1E-04
Aksaray	1.2E-06	1.7E-05	9.1E-05	1.2E-05	3.0E-05	Konya	5.5E-06	1.2E-04	6.7E-04	7.3E-05	1.4E-04
Amasya	8.5E-07	1.3E-05	8.0E-05	1.0E-05	2.5E-05	Kütahya	1.7E-06	2.4E-05	1.9E-04	1.6E-05	4.4E-05
Ankara	1.0E-05	5.9E-04	1.9E-03	2.1E-04	2.9E-04	Kırklareli	1.2E-06	2.0E-05	8.2E-05	1.2E-05	2.7E-05
Antalya	5.6E-06	1.9E-04	6.0E-04	1.1E-04	1.5E-04	Kırıkkale	8.5E-07	1.7E-05	8.3E-05	8.2E-06	2.3E-05
Ardahan	3.7E-07	4.2E-06	2.1E-05	1.8E-06	8.9E-06	Kırşehir	7.3E-07	1.0E-05	5.8E-05	6.8E-06	1.9E-05
Artvin	9.7E-07	6.8E-06	4.1E-05	4.0E-06	1.6E-05	Malatya	2.3E-06	5.0E-05	2.6E-04	2.6E-05	5.4E-05
Aydın	2.8E-06	6.3E-05	2.7E-04	3.8E-05	7.0E-05	Manisa	3.4E-06	7.7E-05	3.5E-04	4.5E-05	9.1E-05
Ağrı	1.1E-06	1.5E-05	7.7E-05	9.0E-06	3.4E-05	Mardin	1.5E-06	2.6E-05	1.4E-04	2.1E-05	6.8E-05
Balıkesir	3.0E-06	6.4E-05	3.1E-04	4.0E-05	8.3E-05	Mersin	3.2E-06	9.8E-05	4.3E-04	6.2E-05	1.1E-04
Bartın	3.7E-07	7.3E-06	4.7E-05	6.4E-06	1.6E-05	Muğla	2.7E-06	6.2E-05	2.2E-04	3.8E-05	6.9E-05
Batman	1.5E-06	2.3E-05	1.5E-04	1.5E-05	4.3E-05	Muş	8.5E-07	1.1E-05	6.5E-05	6.1E-06	2.8E-05
Bayburt	1.2E-07	3.8E-06	2.4E-05	1.6E-06	8.3E-06	Nevşehir	1.2E-06	1.2E-05	7.3E-05	9.7E-06	2.2E-05
Bilecik	9.7E-07	8.5E-06	5.4E-05	5.5E-06	1.7E-05	Niğde	9.7E-07	1.3E-05	7.3E-05	1.0E-05	2.5E-05
Bingöl	9.7E-07	9.0E-06	6.6E-05	6.8E-06	2.3E-05	Ordu	2.2E-06	3.5E-05	1.8E-04	2.3E-05	5.7E-05
Bitlis	9.7E-07	1.2E-05	8.7E-05	6.5E-06	3.0E-05	Osmaniye	1.2E-06	1.9E-05	1.1E-04	1.8E-05	3.8E-05
Bolu	1.3E-06	2.2E-05	1.1E-04	1.1E-05	2.5E-05	Rize	1.3E-06	2.0E-05	9.5E-05	1.0E-05	2.6E-05
Burdur	9.7E-07	1.0E-05	6.8E-05	9.3E-06	2.3E-05	Sakarya	2.2E-06	4.8E-05	2.2E-04	2.8E-05	6.6E-05
Bursa	5.1E-06	1.7E-04	7.3E-04	9.3E-05	1.6E-04	Samsun	3.2E-06	9.0E-05	4.3E-04	4.5E-05	9.1E-05
Denizli	2.8E-06	6.7E-05	2.6E-04	4.0E-05	6.2E-05	Siirt	9.7E-07	1.1E-05	6.4E-05	7.4E-06	2.5E-05
Diyarbakır	3.4E-06	7.9E-05	4.2E-04	4.3E-05	1.1E-04	Sinop	8.5E-07	8.3E-06	5.9E-05	6.8E-06	2.0E-05
Düzce	1.1E-06	2.1E-05	8.1E-05	9.9E-06	2.3E-05	Sivas	2.4E-06	3.4E-05	2.2E-04	1.9E-05	5.0E-05
Edirne	1.3E-06	3.0E-05	1.5E-04	1.5E-05	3.0E-05	Tekirdağ	2.4E-06	5.1E-05	2.2E-04	2.8E-05	6.2E-05
Elâzığ	1.6E-06	3.8E-05	2.2E-04	1.6E-05	4.4E-05	Tokat	1.8E-06	2.6E-05	1.8E-04	1.8E-05	4.1E-05
Erzincan	1.2E-06	1.4E-05	6.3E-05	5.7E-06	1.9E-05	Trabzon	2.7E-06	5.5E-05	2.9E-04	2.8E-05	6.0E-05
Erzurum	2.6E-06	4.2E-05	3.0E-04	2.1E-05	6.1E-05	Tunceli	7.3E-07	3.9E-06	2.2E-05	1.8E-06	1.1E-05
Eskişehir	1.8E-06	6.4E-05	3.2E-04	3.3E-05	5.5E-05	Uşak	9.7E-07	1.7E-05	9.5E-05	1.1E-05	2.4E-05
Gaziantep	4.0E-06	1.0E-04	5.2E-04	5.8E-05	1.2E-04	Van	1.8E-06	4.1E-05	2.7E-04	2.2E-05	6.9E-05
Giresun	2.2E-06	2.2E-05	1.5E-04	1.5E-05	3.8E-05	Yalova	8.5E-07	1.5E-05	6.4E-05	8.0E-06	2.0E-05
Gümüşhane	7.3E-07	5.7E-06	3.3E-05	3.1E-06	1.4E-05	Yozgat	1.9E-06	1.7E-05	1.1E-04	1.0E-05	3.7E-05
Hakkâri	6.1E-07	1.0E-05	4.3E-05	3.7E-06	2.8E-05	Zonguldak	1.5E-06	3.0E-05	1.8E-04	1.8E-05	3.9E-05
Hatay	2.9E-06	7.3E-05	3.6E-04	5.1E-05	1.3E-04	Çanakkale	1.7E-06	3.3E-05	1.6E-04	1.7E-05	3.9E-05
Isparta	1.8E-06	3.5E-05	1.8E-04	1.6E-05	3.3E-05	Çankırı	1.1E-06	7.0E-06	4.0E-05	4.9E-06	1.6E-05
Iğdır	4.9E-07	6.4E-06	3.5E-05	4.2E-06	1.6E-05	Çorum	1.9E-06	2.3E-05	1.5E-04	1.5E-05	4.0E-05
Kahramanmaraş	2.3E-06	4.6E-05	2.8E-04	3.1E-05	7.0E-05	İstanbul	2.8E-05	1.3E-03	4.0E-03	5.3E-04	9.2E-04
Karabük	7.3E-07	1.4E-05	6.8E-05	7.0E-06	2.1E-05	İzmir	7.7E-06	3.7E-04	1.2E-03	1.6E-04	2.3E-04
Karaman	7.3E-07	1.1E-05	6.1E-05	8.1E-06	2.0E-05	Şanlıurfa	2.4E-06	6.2E-05	3.6E-04	5.5E-05	1.3E-04
Kars	9.7E-07	1.2E-05	6.5E-05	5.0E-06	2.2E-05	Şırnak	8.5E-07	1.5E-05	7.2E-05	8.6E-06	4.2E-05
Kastamonu	2.1E-06	1.4E-05	8.9E-05	9.9E-06	3.5E-05						

Following the computation of the weighted normalized values, the analysis continues by calculating final performance scores using the COPRAS method. First, the aggregated cost-type performance values (S_i^-) are calculated to quantify the total disadvantage associated with each alternative. These are followed by the calculation of the relative significance scores (Q_i), which integrate both benefit and cost perspectives in the evaluation process. To make the results more interpretable and comparable across provinces, the normalized priority values (NQ_i) are derived by scaling the Q_i values into the [0, 1] range. This normalization allows a clearer understanding of the relative performance of each alternative, with values closer to 1 indicating better performance. The complete results, including S_i^-, Q_i, NQ_i, and the resulting rankings, are presented in Table 13.

Table 13. COPRAS Rankings of Alternatives

Province	S_i^-	Q_i	NQ_i	Ranking	Province	S_i^-	Q_i	NQ_i	Ranking
Ardahan	3.7E-05	33.4	1	1	Batman	2.3E-04	5.25	0.15	42
Bayburt	3.8E-05	32.3	0.96	2	Adıyaman	2.4E-04	5.18	0.15	43
Tunceli	4.0E-05	30.9	0.92	3	Çanakkale	2.5E-04	4.99	0.14	44
Gümüşhane	5.6E-05	21.8	0.65	4	Mardin	2.6E-04	4.79	0.14	45
Iğdır	6.2E-05	19.8	0.59	5	Tokat	2.6E-04	4.66	0.13	46
Çankırı	6.9E-05	17.7	0.53	6	Zonguldak	2.6E-04	4.65	0.13	47
Artvin	7.0E-05	17.6	0.52	7	Isparta	2.7E-04	4.61	0.13	48
Bartın	7.7E-05	16.0	0.47	8	Kütahya	2.7E-04	4.51	0.13	49
Kilis	7.9E-05	15.6	0.46	9	Ordu	3.0E-04	4.09	0.12	50
Hakkari	8.6E-05	14.3	0.43	10	Afyonkarahisar	3.1E-04	3.99	0.11	51
Bilecik	8.6E-05	14.3	0.42	11	Elazığ	3.2E-04	3.79	0.11	52
Sinop	9.5E-05	12.9	0.38	12	Sivas	3.2E-04	3.79	0.11	53
Kırşehir	9.5E-05	12.9	0.38	13	Sakarya	3.7E-04	3.36	0.10	54
Karaman	1.0E-04	12.2	0.36	14	Tekirdağ	3.7E-04	3.34	0.10	55
Erzincan	1.0E-04	11.9	0.35	15	Muğla	4.0E-04	3.10	0.09	56
Kars	1.1E-04	11.7	0.35	16	Malatya	4.0E-04	3.09	0.09	57
Bingöl	1.1E-04	11.6	0.34	17	Van	4.1E-04	3.01	0.09	58
Yalova	1.1E-04	11.3	0.33	18	Erzurum	4.2E-04	2.91	0.08	59
Siirt	1.1E-04	11.3	0.33	19	Kahramanmaraş	4.3E-04	2.88	0.08	60
Karabük	1.1E-04	11.1	0.33	20	Denizli	4.3E-04	2.86	0.08	61
Burdur	1.1E-04	11.0	0.33	21	Trabzon	4.3E-04	2.85	0.08	62
Muş	1.1E-04	11.0	0.32	22	Aydın	4.5E-04	2.75	0.08	63
Nevşehir	1.2E-04	10.3	0.31	23	Eskişehir	4.7E-04	2.59	0.07	64
Niğde	1.2E-04	10.0	0.29	24	Balıkesir	5.0E-04	2.45	0.07	65
Amasya	1.3E-04	9.54	0.28	25	Manisa	5.6E-04	2.18	0.06	66
Kırıkkale	1.3E-04	9.33	0.27	26	Hatay	6.1E-04	2.01	0.06	67
Düzce	1.4E-04	9.05	0.27	27	Şanlıurfa	6.1E-04	2.01	0.06	68
Ağrı	1.4E-04	9.04	0.27	28	Kayseri	6.2E-04	1.97	0.05	69
Bitlis	1.4E-04	9.02	0.27	29	Diyarbakır	6.6E-04	1.87	0.05	70
Şırnak	1.4E-04	8.84	0.26	30	Samsun	6.6E-04	1.87	0.05	71
Kırklareli	1.4E-04	8.69	0.26	31	Mersin	7.0E-04	1.75	0.05	72
Uşak	1.5E-04	8.28	0.24	32	Kocaeli	7.5E-04	1.63	0.04	73
Kastamonu	1.5E-04	8.22	0.24	33	Gaziantep	8.0E-04	1.54	0.04	74
Aksaray	1.5E-04	8.10	0.24	34	Adana	9.2E-04	1.33	0.03	75
Rize	1.5E-04	8.02	0.24	35	Konya	1.0E-03	1.21	0.03	76
Bolu	1.7E-04	7.35	0.21	36	Antalya	1.0E-03	1.17	0.03	77
Yozgat	1.8E-04	6.78	0.20	37	Bursa	1.2E-03	1.05	0.03	78

Osmaniye	1.8E-04	6.67	0.19	38	İzmir	2.0E-03	0.62	0.01	79
Giresun	2.2E-04	5.50	0.16	39	Ankara	3.0E-03	0.40	0.01	80
Edirne	2.3E-04	5.35	0.16	40	İstanbul	6.7E-03	0.18	0.00	81
Çorum	2.3E-04	5.34	0.16	41					

The choropleth map presented in Figure 1 has been generated based on the normalized priority values (NQ_i) obtained in Table 13. These scores reflect the final stage of the COPRAS method, where all criteria were aggregated into a unified performance index scaled between 0 and 1. In this visualization, darker shades represent provinces with higher NQ_i scores, indicating better overall performance in terms of healthcare accessibility and workforce distribution based on the integrated weights derived from ENTROPY and SWARA methods.

The results reveal that Bayburt, Ardahan, and Tunceli are among the top-performing provinces, reflecting relatively higher adequacy in their healthcare services when adjusted for population. These provinces likely benefit from better resource distribution relative to their population size. Conversely, Istanbul, despite its extensive infrastructure, appears in lighter tones, suggesting that high population density negatively affects per capita healthcare indicators. This figure supports the numerical findings presented in Table 13, providing a spatial interpretation of inter-provincial disparities in healthcare system performance.

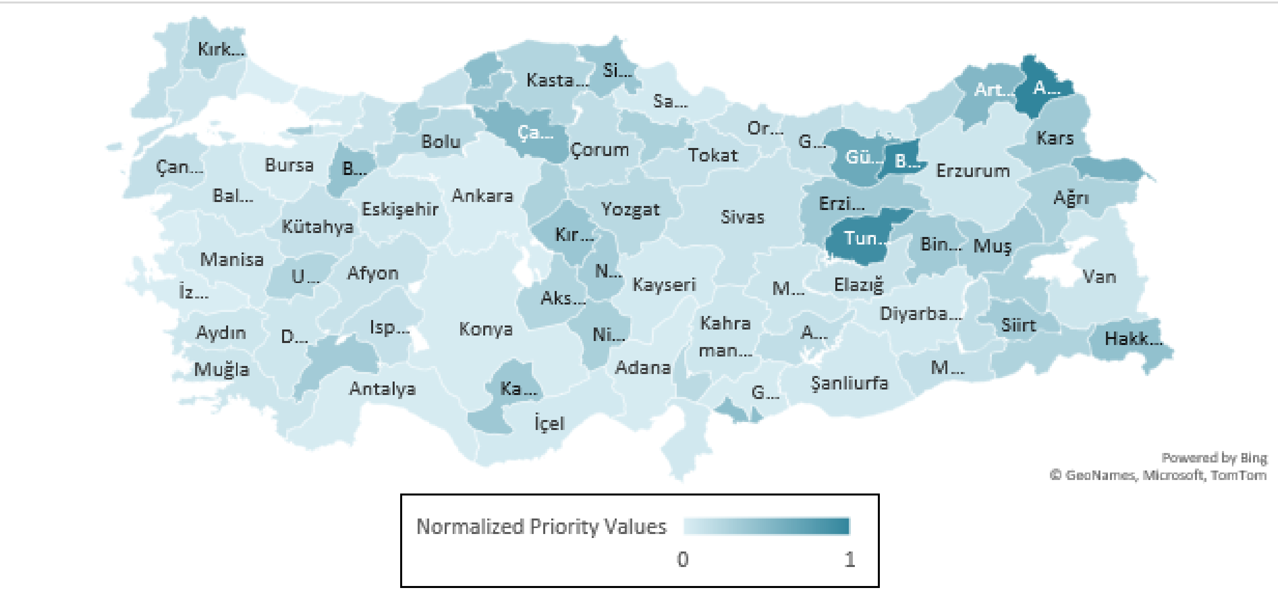

Figure 2. Performances of Provinces

4. RESULTS

This study evaluates the healthcare performance of 81 provinces in Turkey by employing a hybrid multi-criteria decision-making (MCDM) model. The analysis was based on five criteria related to healthcare infrastructure and personnel in the year 2021. These include the number of hospitals, specialist physicians, nurses, pharmacists, and general practitioners. All values were adjusted based on population in order to enable fair and meaningful inter-provincial comparisons.

Objective weights of the criteria were determined using the ENTROPY method, which quantifies the discriminative power of each criterion based on data variability. Subjective weights were derived from expert evaluations using the SWARA method. To ensure that both data-driven and expert-based insights are reflected in the evaluation process, a combined weight set was created using equal contribution from both sources by setting λ = 0.5. These integrated weights were subsequently used in the COPRAS method to rank the provinces.

The findings reveal significant disparities in healthcare performance across regions. Provinces such as Bayburt, Ardahan, and Tunceli exhibited the highest normalized performance scores. On the other hand, Istanbul was identified as the province with the lowest performance relative to is considered. This outcome highlights the importance of adopting population-adjusted performance metrics to avoid overestimating service adequacy in densely populated regions.

In contrast to previous studies in the healthcare sector that often rely solely on descriptive statistics or single-weighting mechanisms, this research applies a formal MCDM structure supported by real personnel data. The integration of ENTROPY, SWARA, and COPRAS into a unified framework represents a novel methodological contribution. According to the reviewed literature, no prior study has implemented this specific combination in the context of evaluating provincial healthcare performance in Türkiye.

The results offer a practical foundation for decision-makers to identify underperforming regions and guide the equitable allocation of healthcare resources. Moreover, the proposed model is adaptable to other sectors requiring structured multi-criteria evaluation based on both empirical data and expert input.

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