Advances in Industrial Engineering, December 2024, 58(2): 371-390
DOI: 10.22059/AIE.2024.379263.1900

RESEARCH PAPER

Enhancing Human Development Assessment through Multi-Criteria Decision Making: A Case Study of Health Status and Services in West Azerbaijan, Iran

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Received: 11 July 2024, Revised: 10 August 2024, Accepted: 11 August 2024

Abstract

This study investigates the Human Development Index (HDI), a composite measure developed by the United Nations Development Program to evaluate human development through life expectancy, education, and income. This research aims to assess the health status and services across 17 cities in West Azerbaijan Province, Iran, using multi-criteria decision-making (MCDM) techniques: TOPSIS, MOORA, ARAS, and COPRAS. Eight health indicators, including primary medical care centers, laboratories, active beds, pharmacies, general practitioners, specialists, subspecialists, and dentists, were used for the ranking. The Shannon entropy method was applied to determine the weights of these indicators. The results reveal significant disparities in health service distribution, with Urmia, Khoy, and Miandoab having the best health services, while Poldasht, Chaldoran, and Chaypareh are the most deprived. The study employs the Spearman rank correlation coefficient to validate the rankings and utilizes the utility interval aggregation method to enhance reliability. Managerial insights suggest that policymakers should prioritize equitable distribution of health services to mitigate disparities and promote balanced regional development. Effective resource allocation and targeted interventions in underserved areas are crucial for improving overall human development.

Keywords: Human Development Index, Life Expectancy, MCDM, Health Indicators, Utility Interval Method.

Introduction

Human development can be defined as the process of enhancing individuals' freedom and opportunities while elevating their well-being. Economist Mahbub ul Haq created this concept, asserting that human development aims to enrich human life. He argued that the core goal of development, which is to improve people's lives, is not adequately captured by current metrics of human advancement (Hirai and Hirai, 2017).

An effort to create an index for better understanding and assessing progress in nations throughout the world was supported by the United Nations Development Program (UNDP) in 1989. This endeavor produced the Human Development Index (HDI) (Human Development Report, 2023). The HDI is a combination of three dimensions, including life expectancy,

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education, and national income, measured by four indicators: life expectancy at birth, average years of schooling, life expectancy, and per capita gross national income. HDI is the geometric mean of the normal indices listed for each dimension. Health, education, and standard of living are measured by life expectancy at birth, the average years of education for adults, the expected years of education for school children, and gross national income, respectively (UNDP, 2023).

HDI emphasizes that not only economic growth but also the people and their abilities should be the main indicator for assessing a country's development. Over the past two decades, HDI has become a common tool for assessing a country or region's level of human development. Its popularity is due to two main reasons. The first reason includes quality of life, education, and life expectancy, not the elements included in standard income measurements. The second reason is that it is relatively easy to calculate and requires less data, so it can be calculated for many developing countries. However, the criteria for measuring human development also have weaknesses. The main problem is that it considers only the three elements of economic education, life expectancy, and income. It does not include other important elements such as income inequality, gender inequality, disease, pollution, or economic security (Investopedia, 2016).

Examining HDI in different countries can answer questions about that country's policies, including why countries with equal per capita Gross Domestic Product (GDP) have different HDIs. The imbalance between opportunities and choices of individuals is rooted in differences in income as well as education level, health status, and access to technology. Gaps in human development represent unequal opportunities in access to education, health, employment, credit, and natural resources. Inequality is not only normatively wrong; it is also problematic. This gap can fuel extremism and undermine support for inclusive and sustainable development. High inequality may lead to adverse consequences for social cohesion and the quality of institutions and policies, reducing human development progress. When there is inequality in the distribution of health, education, and income in a society, the HDI of the society is less than the total HDI (Kovacevic et al., 2018).

Life expectancy, one of the three dimensions of HDI, is the average number of years a newborn is expected to live if the community's living conditions and mortality patterns are stable. A long and healthy life is measured by life expectancy. In terms of health, there are widespread inequalities in different countries with different levels of HDI. The average life expectancy in countries with a very high human development index is 79.5 years, while in countries with a low human development index, it is 60.8 years (Sayari et al., 2022).

Calculating life expectancy at birth makes it possible to report life expectancy at other ages to track the health status of specific age groups in the population. Life expectancy at birth can be attributed to various factors, including improved lifestyles and better education, as well as greater access to quality health services (Banerjee and Mukherjee, 2022). Items such as lost life expectancy (difference between life expectancy and healthy life expectancy expressed as a percentage of life expectancy at birth), physicians (number of general and specialist physicians per 10,000 people), hospital beds (number of hospital beds available per 10,000), newborn and children health, adult health (mortality by sex, and infectious and Non-infectious diseases) are cited as an indicator of health in HDI (Kovacevic et al., 2018). Since a healthy human being is known as the axis of sustainable development, the health system and its subsystems are among the most significant pillars of societal development (Shetaban et al., 2020). The poor health of employees and their life expectancy have a negative impact on economic growth (Qin et al., 2022). Health is a major factor in people's well-being. In OECD countries, life expectancy has remarkably increased over the past 50 years due to growth in health spending, lifestyle, education, and environmental changes. Chronic (non-communicable) diseases such as cancer, diabetes, and chronic respiratory diseases are today's most important determinants of disability and mortality in OECD countries (Voukelatou et al., 2021).

Even though the HDI is comprehensive in that it simultaneously pays attention to the economic, social, and biological components, some academics and policymakers have long criticized it. Some of these complaints include calculating the index, which involves averaging the three health, education, and income dimension indicators with equal weights (Land, 2015). Consequently, to address some of the weaknesses associated with the index, this study employs the multi-criteria decision-making (MCDM) technique as an alternative to the average way of ranking cities of West Azerbaijan Province in Iran in terms of health status and health services of the cities (Mansori et al., 2018; Reuter-Oppermann et al., 2019). According to the literature, eight health indicators are introduced. Then, as a case study, 17 cities of West Azerbaijan province are ranked using MCDM techniques such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Objective Optimization Ratio Analysis (MOORA), Additive Ratio Assessment (ARAS), and Complex Proportional Assessment (COPRAS). We calculate the correlation between the results of our MCDM techniques through the Spearman correlation coefficient. Given the minor discrepancies observed among the rankings obtained from four different methods, we adopt the utility interval method to establish a unique and academically robust city ranking. Significant gaps persist despite substantial research on the relationship between HDI and health outcomes. This paper addresses these gaps by thoroughly analyzing diverse health indicators influenced by HDI and employing advanced MCDM techniques for a nuanced assessment of regional health development. It highlights issues of healthcare equity and accessibility, identifies regions with significant disparities, and proposes targeted interventions. By integrating theoretical frameworks with practical case studies, this study offers valuable insights that bridge theory and practice, thereby informing and enhancing health policy decisions. The main objectives of this research can be summarized as follows:

- To rank cities of West Azerbaijan Province in Iran in terms of health status and health services of the cities;
- To help decision-makers identify deprived cities and take action to eliminate deprivation and poverty by making supportive decisions.

This paper is organized as follows. In section 2, the related work with HDI and health and the application of MCDM in healthcare is presented. In section 3, the methodology of the research is described. Our four MCDM techniques and Shannon entropy method are presented in this section. The results of four MCDM techniques are shown in section 4. Finally, section 5 concludes this paper and suggests some future research directions.

Literature Review

In this section, we comprehensively examine existing research on the relationship between HDI and various health outcomes. We explore how HDI impacts disease prevalence, mortality rates, and access to healthcare across different regions. Additionally, we review the application of MCDM techniques in healthcare, highlighting studies that have utilized these methods to address disparities in health indicators and improve access to health services. Through this literature review, we aim to identify gaps in the current research and establish a foundation for our subsequent analysis.

HDI and Health

A nuanced narrative emerges in exploring the intricate relationship between health outcomes and socio-economic factors, connecting diverse health issues with various dimensions of HDI and life expectancy. The studies shed light on how different diseases and health challenges are intertwined with developmental indices, offering insights into regional disparities and broader global patterns. This comprehensive investigation reveals how high and low HDI environments, spanning both developed and developing countries, influence disease prevalence, healthcare access, and overall health outcomes.

The distribution of cancer varies globally based on HDI levels. Hassanipour-Azgomi et al. (2016) noted a positive relationship between prostate cancer and HDI, observing higher rates and mortality in high HDI countries. This connection can be due to diet, lifestyle, extensive clinical examinations, and, most importantly, access to preventive services and cancer registration systems. It is also related to life expectancy, which is a component of HDI, because prostate cancer is closely linked to age, and most people with the disease are over 80 years old. In general, people with higher education, better diets, and more physical activity are less likely to contract infectious diseases and more likely to develop non-communicable diseases. Mansori et al. (2018) highlighted that due to the lack of a regular screening program and the very low quality of screening in developing countries, cervical cancer has become a public health problem in these areas. Khazaei et al. (2019) addressed skin cancer as one of the most common cancers in the world that is associated with HDI. Increasing HDI increases access to health services and early detection and treatment of the disease in its early stages, resulting in reduced mortality. In less developed countries, access to more specialized healthcare facilities and robust monitoring systems is essential for early diagnosis and mortality reduction. Silva et al. (2023) identified a positive correlation between HDI and pancreatic cancer mortality rates in Brazil, with higher HDI regions showing increased mortality rates, reflecting global patterns. Chou et al. (2024) investigated the link between HDI, health expenditures, and breast cancer outcomes. They found that higher HDI and health expenditures were associated with higher breast cancer incidence but lower mortality rates and mortality-to-incidence ratios (MIRs). Similarly, Da Silva et al. (2024) studied gynecological cancers in Sergipe, Brazil, where despite a decline in incidence, mortality rates for cervical, ovarian, and uterine cancers increased, underscoring the need for improved prevention and treatment strategies in regions with medium HDI.

In terms of non-communicable diseases, Ameye and Swinnen (2019) examined the increasing rates of obesity in both high and low-income countries, noting a complex, non-linear relationship between income and HDI. Obesity, while not directly linked to cancer in this context, impacts overall health and contributes to various non-communicable diseases. Ataey et al. (2020) further explored obesity, showing significant associations with HDI components such as life expectancy and education levels, and highlighted that high gender inequality can increase obesity prevalence, particularly among women.

Infant mortality is a critical indicator of child health and overall development. Akinlo and Sulola (2019) emphasized that infant mortality rates reflect maternal and child healthcare quality. Anele et al. (2021) also examined the impact of Municipal HDI and maternal education on infant mortality in Porto Alegre, Brazil, finding that lower MHDI and maternal education levels correlated with higher infant mortality rates. Dearie et al. (2021) emphasized that infant mortality rate and adult mortality are comprehensive measures of overall health. This perspective supports the broader view that HDI components are integral to understanding and improving health outcomes across various disease categories. Figueiredo et al. (2022) found that Niterói, Brazil, achieved low infant mortality rates due to high HDI and the early implementation of a strong primary care network, highlighting the impact of socio-economic factors on child survival. Mohammadian-Hafshejani et al. (2024) analyzed childhood leukemia globally, finding a significant positive correlation between the Age-Standardized Incidence Rate (ASIR) and HDI, although HDI less influenced mortality rates.

Life expectancy and chronic diseases also play a crucial role in health outcomes. Zhu et al. (2016) noted that over recent decades, coronary heart disease prevalence has increased in developing countries while decreasing in developed countries. This trend reflects broader shifts in health outcomes associated with different levels of development. Wan et al. (2019) reported that life expectancy decreases as chronic kidney disease and cardiovascular disease severity increases, resulting in more deaths among younger patients. This finding underscores the importance of addressing chronic conditions to improve life expectancy. The prevalence of coronary heart disease has shown divergent trends across the globe.

Research by Mejia-Pailles et al. (2020) examined the global impact of Human Immunodeficiency Viruses (HIV) and Acquired Immunodeficiency Syndrome (AIDS), highlighting the continued significance of monitoring these epidemics and the effectiveness of interventions. Meanwhile, Raleigh (2019) discussed how diseases occurring at older ages, linked to HDI, contribute to slower reductions in life expectancy.

The Application of MCDM in Healthcare

Multi-criteria decision-making (MCDM) aims to determine the best alternative by considering multiple criteria in the selection process (Taherdoost and Madanchian, 2023). MCDM techniques have been widely used in fields such as supply chain management, health, economics, industrial engineering, and environmental sciences (Bhattacharya et al., 2020; Pathan et al., 2022; Limpianchob et al., 2022). These methodologies address decision-making challenges in various areas related to HDI, including health services, urban planning, development ranking, and innovation evaluation. Each MCDM method offers unique advantages tailored to specific analytical needs, enabling detailed assessments and informed decision-making.

TOPSIS is one of the techniques that many studies have employed to address different problems. Abolhallaje et al. (2014) investigated regional inconsistencies in medical centers across Markazi province. The study examined 15 health indicators, including the number of laboratories, staff of active rural health houses, general practitioners, specialists, paramedics, active hospital beds, pharmacies, dentists, and urban health centers. Using the TOPSIS technique for ranking, the results indicated a significant disparity in access to health facilities among the cities within the Markazi province.

Lack of health facilities and human resources and their inadequate distribution in urban and rural areas are major problems in health services in third-world countries. Mahboubi et al. (2020) aimed to determine the development rate of Abadan, Khorramshahr, and Shadegan cities regarding access to health indicators. Using a numerical taxonomy model showed that Abadan is less developed, Shadegan is less developed, and Khorramshahr is less developed. Omrani et al. (2020) proposed a new approach to calculating semi-HDI scores. First, new and additional criteria are selected in each dimension of health, education, and standard of living. Then policy-maker preferences are considered to determine the weighting of the criteria in each dimension using the best worst method (BWM), and then the multi MOORA assign method is applied to rank provinces of Iran in each dimension. The semi-HDI values of the provinces are calculated based on the geometric mean of healthy living, the education of the population, and the standard of living. According to the results, Kohgiluyeh, Boyer-Ahmad, and Sistan and Balochistan provinces are Iran's most and least developed provinces, respectively.

Zamani and Omrani (2022) presented a complete information principal component analysis (CIPCA)-Imprecise Data Envelopment Analysis (IDEA) approach to determine the degree of development of cities with uncertain data. The authors used PCA to reduce the number of indicators, and their output was then used as a set of new indicators with lower and upper bounds. Therefore, these indicators are considered IDEA indicators, and finally, they used the IDEA model to rank cities. The proposed approach is applied to nine cities of Kurdistan Province, and the degree of development for each city is finally calculated. The results showed that Bijar City takes first place in development in the overall ranking, and Baneh ranks ninth. Goker et al. (2022) developed a fuzzy MCDM method combining quality function deployment and DEA to rank countries based on HDI dimensions and sustainable development goals. The approach applied to Latin American countries used fuzzy weighted averages and a house of quality to account for criterion interactions. Peru, Chile, and Costa Rica ranked highest. Rankings were positively correlated with HDI, though variations arose from the broader scope and interactions considered in the methodology.

Tunsi et al. (2023) developed an innovation-based HDI for G8 countries using the PROMETHEE II MCDM method, incorporating technological criteria such as the Global Innovation Index (GII). Seven technological indicators from the World Bank and the GII were used to reformulate the HDI. Results showed significant ranking shifts: the USA moved from 5th to 1st place, while Canada dropped from 2nd to 6th. The new index highlighted how incorporating technological dimensions altered country rankings compared to the traditional HDI, demonstrating the potential of MCDM methods for creating more nuanced development indexes.

MCDM techniques are used in a range of health issues, and we have reviewed the applications of MCDM techniques in Table 1. Based on Table 1, some researchers have examined the level of development of different cities in terms of health indicators in recent years. Equal distribution of health facilities to increase people's access to services is one of the main pillars of improving health. Some researchers have tried to rank the cities of some provinces of Iran in terms of health indicators. As can be seen, very few articles used MCDM methods in terms of HDI, especially in recent years.

Table 1. MCDM application in HDI, healthcare sector

Article	Purpose	Applied methods
Abolhallaje et al. (2014)	Examine regional disparities in health care facilities in Markazi Province, Iran.	TOPSIS
Mahboubi et al. (2020)	Determine the development rate of Iranian cities regarding access to health indicators.	Numerical taxonomy
Omrani et al. (2020)	Propose a new approach to calculate semi-HDI scores.	BWM, Multi MOORA
Zamani and Omrani (2022)	Find the development degree of cities with uncertain data.	IDEA
Goker et al. (2022)	Rank Latin American countries by incorporating imprecise data and inner dependence among evaluation criteria.	DEA
Tunsi et al. (2023)	Propose an enhanced version of the HDI that includes technological dimensions and innovation metrics for benchmarking human development among countries.	PROMETHEE II
This paper	Rank Cities in Azerbaijan Province, Iran, based on the health sector of the HDI.	TOPSIS, MOORA, ARAS and COPRAS

Literature Gap and Our Contribution

While a substantial body of research examines the relationship between HDI and health outcomes, several gaps remain unaddressed. Our paper aims to fill these gaps by introducing several novel elements to the analysis:

1. **Comprehensive HDI and Health Analysis:** Many studies have focused on specific diseases or health outcomes in relation to HDI. However, our research expands this scope to include a broad spectrum of health indicators, such as obesity, chronic kidney disease, and maternal health, providing a more comprehensive understanding of how HDI influences overall health.
2. **Application of MCDM Techniques:** Previous research often relies on basic statistical methods to analyze the relationship between HDI and health outcomes. Our study stands out by employing advanced MCDM techniques, which are used less in the literature, to evaluate and rank the health development levels of different regions. This approach allows for a more nuanced and holistic analysis, considering multiple health criteria simultaneously.
3. **Focus on Equity and Accessibility:** Although the equitable distribution of healthcare resources is a critical aspect of improving health outcomes, it has not been extensively

studied in relation to HDI. Our paper emphasizes this aspect by using MCDM methods to identify regions with significant healthcare disparities and propose targeted interventions to enhance healthcare access and outcomes.

4. **Case Study Application:** While theoretical frameworks and statistical analyses are common in existing literature, there is a lack of practical applications demonstrating these methods' real-world utility. Our research includes case studies that showcase the practical implementation of MCDM techniques in informing health policy decisions, thereby bridging the gap between theory and practice.

By addressing these gaps, our paper contributes to the literature by providing a more detailed and practical analysis of the relationship between HDI and health, offering valuable insights for researchers and policymakers aiming to reduce health disparities and improve population health outcomes.

Methodology

It is preferred to aggregate the same type of MCDM techniques based on the input information by nature of MCDM combination methods. Turskis and Zavadskas (2010) and Varmazyar et al. (2016) offered different MCDM techniques to solve complex problems. The first type is a quantitative measurement-based technique, such as TOPSIS, SAW, MOORA, ARAS, and COPRAS. The second type is techniques based on early qualitative measures like AHP, ANP, etc. The third oneth is comparative preference techniques based on side-by-side evaluation of options like PROMETHEE and ELECTERE. The last one is techniques based on qualitative assessments that are not translated into numerical values, such as verbal decision-making analysis.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widespread and common multi-objective decision-making technique based on the concepts of Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). The first ideal solution maximizes total profit and minimizes total costs, and the second ideal solution minimizes profit and maximizes costs (Hwang and Yoon, 1981). TOPSIS uses analytical methods of Euclidean distance functions on normalized vectors of positive (Output) and negative (input) criteria. Determining the weights that identify the importance of each criterion (benefits and costs or just outputs and inputs) is a fundamental step already defined by the research decision-maker. Therefore, TOPSIS allows the acceptance of multiple variables and does not require prior production performance specifications commensurate with the complexity of healthcare services (Araujo et al., 2018). TOPSIS represents an MCDM problem with m alternatives as a geometric system with m points in the next n space. The main concept of this technique is that the selected alternative should have the shortest geometric distance from PIS and the highest geometric distance from NIS.

The TOPSIS steps are as follows:

Step 1. Normalizing the decision matrix of the vector method.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_i j^2}} \tag{1}$$

Step 2. Obtaining the weighted normalized matrix by multiplying the weights of the criteria in the corresponding column.

$$t_{ij} = r_{ij} \times w_j \tag{2}$$

Step 3. Identify the set of positive and negative ideal solutions. A positive ideal solution contains the best values in each index, and a negative one contains the worst ones in each index.

The best value in an index with a positive nature is the largest value and the best value of an index with a negative nature is the lowest value of that index.

$$PIS = A^{+} = \left(Max_i\, U_{ij} \,\middle|\, j \in j^{+}\right), \left(Min_i\, U_{ij} \,\middle|\, j \in j^{-}\right) \tag{3}$$
$$NIS = A^{-} = \left(Max_i\, V_{ij} \,\middle|\, j \in j^{-}\right), \left(Min_i\, V_{ij} \,\middle|\, j \in j^{+}\right) \tag{4}$$

Step 4. Calculate the positive and negative separator sizes for each alternative. This includes the Euclidean distance of each alternative to the positive and negative ideal solutions.

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} (a_{ij} - A_j{}^{+})^2} \tag{5}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} (a_{ij} - A_j{}^{-})^2} \tag{6}$$

Step 5. Find the relative size close to the ideal solution using the separator distances obtained in step 4 using the following equation.

$$C_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \tag{7}$$

If $0 \le C_i \le 1$; The greater the distance of an alternative from the negative ideal solution A^{-} and less than the ideal positive solution A^{+}. The greater the relative proximity of that alternative to the ideal solution C_i, the better the alternative.

If $C_i = 1$, This means that the i alternative is the best in all criteria, or in other words, it has no distance to the positive ideal ($S_i^{+} = 0$).

If $C_i = 0$, This means that the *i* alternative is the worst of all criteria, or in other words, it has no distance to the negative ideal ($S_i^{-} = 0$).

Multi-Objective Optimization Ratio Analysis (MOORA)

Brauers and Zavadskas (2006) introduce the Multi-Objective Optimization Ratio Analysis (MOORA) technique, which has recently been applied in several studies as an MCDM method. The significance coefficient and the ratio system are the two components of this technique with the following steps:

Step1. Construct a decision matrix *(X)* containing the performance of *m* alternatives with respect to *n* attributes.

$$\mathbf{X} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}, \tag{8}$$

where x_{ij} is the performance measure of alternative i^{th} on attribute j^{th}

Step2. According to Brauers et al. (2008) and Chakraborty (2011), calculate the ratio value. The best choice of ratio system is the square root of the sum of squares of each alternative per attribute. The ratio is expressed below:

$$\hat{x}_{ij} = \frac{x_{ij}}{\left[\sum_{i=0}^{m} x_{ij}^2\right]^{1/2}}, \qquad i = 1,\ldots,m; \quad j = 1,\ldots,n. \tag{9}$$

where $\hat{x}_{ij}$ is a dimensionless number in the interval of [0, 1] representing the normalized performance of alternative i^{th} on attribute j^{th}. The ratio system calculates the overall performance of each alternative as the difference between the sums of its normalized performances.

Step3. For multi-objective optimization, these responses are added in case of maximization and subtracted in case of minimization based on Eq.(10).

$$Y_j = \sum_{j=1}^{k} \hat{x}_{ij} - \sum_{j=k+1}^{n} \hat{x}_{ij}, \qquad j = 1, \ldots, n. \tag{10}$$

where k is the number of attributes to be maximized.

In order to show the significance of each attribute, the weights are considered (significance coefficient). Thus the Eq.(10) becomes Eq.(11).

$$Y_j = \sum_{j=1}^{k} w_j \hat{x}_{ij} - \sum_{j=k+1}^{n} w_j \hat{x}_{ij}, \qquad j = 1, \ldots, n. \tag{11}$$

The Y_j value could be positive or negative depending on the beneficial and non-beneficial attributes in the decision matrix. Therefore, the best alternative has the highest value.

Additive Ratio Assessment (ARAS)

Zavadskas and Turskis (2010) propose the Additive Ratio Assessment (ARAS) technique as an MCDM method. The following steps demonstrate the process**:**

Step1. Forming the decision-making matrix *(*DMM*)* is the initial stage. The following DMM of preferences *(xij)* for *m* alternatives (rows) rated on *n* sign full criteria (columns):

$$\mathbf{X} = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}, \tag{12}$$

x_{0j} is the optimal value of j criterion.

If th e optimal value of j criterion is unknown, then

$$x_{0j} = \max_i x_{ij}, \text{ if } \max_i x_{ij} \text{ is preferable and } x_{0j} = \min_i x^*_{ij}, \text{ if } \min_i x^*_{ij} \text{ is preferable} \tag{13}$$

The criteria weights *wj*, and the performance values *xij* are viewed as the entries of a *DMM*. Experts decide on the system of criteria as well as the values and initial weights of the criteria. The ratio to the optimal value is utilized in order to avoid the challenges brought on by various criteria dimensions.

Step2. The initial values of all the criteria are normalized.

$$\bar{\mathbf{X}} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix} \tag{14}$$

The criteria, whose preferable values are maxima, are normalized as follows:

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, \qquad i = 0, \ldots, m; \quad j = 1, \ldots, n. \tag{15}$$

The criteria, whose preferable values are minima, are normalized by applying a two-stage procedure:

$$x_{ij} = \frac{1}{x^*_{ij}}, \qquad i = 0,\ldots,m; \quad j = 1,\ldots,n. \tag{16}$$

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, \qquad i = 0,\ldots,m; \quad j = 1,\ldots,n. \tag{17}$$

Step3. In this step, the normalized-weighted matrix is defined. It is possible to evaluate the criteria with weights $0 < wi < 1$. The expert evaluation method is typically used to determine the values of weight *wj* $(\sum_{i=1}^{n} w_j = 1)$.

$$\hat{\mathbf{X}} = \begin{bmatrix} \hat{x}_{01} & \cdots & \hat{x}_{0j} & \cdots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \hat{x}_{i1} & \cdots & \hat{x}_{ij} & \cdots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mj} & \cdots & \hat{x}_{mn} \end{bmatrix}, \qquad i = 0\ldots m; \quad j = 1\ldots n. \tag{18}$$

The following formula is used to calculate each criterion's normalized-weighted values:

$$\hat{x}_{ij} = \bar{x}_{ij} \times w_j, \qquad i = 0\ldots m; \quad j = 1\ldots n. \tag{19}$$

where *wj* is the weight (importance) of the *j* criterion, and *xij* is the normalized rating of the *j* criterion.

Step4. The optimality function values are determined in this step as follows:

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}; \qquad i = 0,\ldots,m. \tag{20}$$

where S_i is the value of the optimality function of i alternative. The biggest value is the best, and the last one is the worst. Therefore, the greater the value of the optimality function S_i, the more effective the alternative. The priorities of alternatives can be determined according to the value S_i. Consequently, evaluating and ranking decision alternatives is convenient when this method is used.

Step5. The degree of the alternative utility is determined by comparing the variant, which is analyzed, with the ideally best one S_0. The equation used for the calculation of the utility degree K_i of each alternative is given below:

$$K_i = \frac{S_i}{S_0}; \qquad i = 0,\ldots,m. \tag{21}$$

where S_i and S_0 are the optimality criterion values, obtained from Eq. (20).

It is clear that the calculated values K_i are in the interval [0, 1] and can be ordered in an increasing sequence, which is the wanted order of precedence. The complex relative efficiency of the feasible alternative can be determined according to the utility function values.

Complex Proportional Assessment (COPRAS)

The Complex Proportional Assessment (COPRAS) technique is an MCDM method that was introduced by Zavadskas and Kaklauskas (2002). This method determines a solution to the positive-ideal and negative-ideal solutions and, therefore, can be considered a compromising

MCDM method. Initially, the COPRAS procedure consists of the following steps:
Step1. Select the influencing criteria describing the alternatives.
Step2. Prepare the decision-making matrix X based on attribute i in the alternative j.

$$\mathbf{X} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}, \tag{22}$$

m is the number of attributes; n is the number of the alternatives compared.
Step3. Determine the weights of the attributes w_i.
Step4. Normalize the decision-making matrix based on Eq.(23).

$$\bar{\mathbf{X}} = \begin{bmatrix} \bar{x}_{11} & \dots & \bar{x}_{1j} & \dots & \bar{x}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix} \tag{23}$$

where $\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$
Step5. Calculate the weighted normalized decision-making matrix $\bar{X}$. The weighted normalized values $\hat{x}_{ij}$ are calculated by Eq.(24).

$$\hat{\mathbf{X}} = \begin{bmatrix} \hat{x}_{11} & \cdots & \hat{x}_{1j} & \cdots & \hat{x}_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \hat{x}_{i1} & \cdots & \hat{x}_{ij} & \cdots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mj} & \cdots & \hat{x}_{mn} \end{bmatrix}, \tag{24}$$

where $\hat{x}_{ij} = \bar{x}_{ij} \times w_j$, $i = 0,\dots,m$; $j = 1,\dots,n$ (w_j is the weight of j^{th} criteria determined in step3).
Step6. Determine the maximizing index (P_j using Eq. (25)) and minimizing index (R_j using Eq. (26)) for each alternative from which the maximum value is optimum.

$$P_j = \sum_{i=0}^{k} \hat{x}_{ij}, \qquad j = 1,\dots,n. \tag{25}$$

$$R_j = \sum_{i=k+1}^{m} \hat{x}_{ij}, \qquad j = 1,\dots,n. \tag{26}$$

where k is the number of attributes that should be maximized.
Step7. Calculate the relative weight of each alternative Q_j.

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j + \sum_{j=1}^{n} R_j}, \qquad j = 1,\dots,n. \tag{27}$$

The highest value of Q_j represents the best alternative.

Shannon Entropy

The Shannon entropy method is an MCDM weight determination model that uses the initial decision matrix to determine decision criteria weights (Yazdani et al., 2020). The Shannon Entropy method is a widely used tool for assessing uncertainty or randomness in datasets, making it valuable across various fields such as environmental science, architectural heritage conservation, healthcare, and medical diagnostics. It offers objective weighting of criteria based on data-driven information, reducing bias in decision-making processes. By measuring uncertainty, Shannon Entropy highlights criteria with greater variability, indicating their importance in decision contexts. Its adaptability across different domains, whether quantitative or qualitative, enhances its utility. In MCDM methods, such as TOPSIS and COPRAS, Shannon Entropy improves the accuracy, robustness, and reliability of outcomes by ensuring that criteria weights reflect the true informational content of the data. This method is used with the following steps:

Step1. The initial matrix is constructed, and the normalization is performed as follows:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad i = 1,2, \dots, m \tag{28}$$

Step2. The entropy value of each criterion is calculated as follows:

$$e_j = -K \sum_{i=1}^{m} r_{ij} \log r_{ij}, \quad j = 1,2, \dots, n \tag{29}$$

This formula $K = \frac{1}{log\, m}$ is a constant that makes sure $0 \leq e_j \leq 1$, in this e_j shows the entropy value for criteria C_j, while m is the number of alternatives.

Step3. The objective weight of each criterion is determined as follows:

$$W_j = \frac{1 - e_j}{\sum_{i=1}^{m}(1 - e_j)}, \quad j = 1,2, \dots, n \tag{30}$$

where W_j indicates the weights of the objectives of each criterion C_j.

Results

The criteria extracted from the relevant literature include primary medical care centers, laboratories, active beds, pharmacies, paramedics, general practitioners per 1,000 people, specialists and subspecialists, and dentists per 10,000 people. We extracted the required data for each index by the city from the statistical yearbook of the 2020 health report (Statistical Center of Iran, 2019). All these criteria are positive, and their high level indicates the good condition of health services in each city. The initial data for 17 provinces' cities are shown in Table 2 to rank by using four proposed techniques: TOPSIS, MOORA, ARAS, and COPRAS. We used MATLAB R2017a to design and execute the techniques.

Result of TOPSIS Technique

We used the TOPSIS technique to rank the province's cities based on the indicators of health services. In the first step, the collected data is normalized. Then, based on the Shannon entropy method, we obtained the weight of the studied criteria, which can be seen in Table 3. According to the Shannon entropy method, active bed (w = 0.138) and pharmacy (w = 0.134) indices have the highest weight, and general practitioner (w = 0.114) and primary care (w = 0.101) indices have the lowest weight, respectively.

After obtaining the normalized decision matrix, we calculated the set of positive ideal solutions and the set of negative ideal solutions. Given that all the studied indices were positive, the positive ideal solution for all indices is equal to the maximum value, and thus, the negative ideal solution is the lowest value of each index. After calculating each index's positive and negative separator sizes in the final step, we obtain a relatively close size to the ideal solution (C) for each alternative according to the formula.

The results of TOPSIS were obtained according to Table 4 and Table 5. These tables show that the best alternative in terms of health service indicators is Urmia (score 1), the second alternative is Khoy (0.2557), the third alternative is Miandoab (0.18), and the worst alternative is Poldasht (0.0155).

Table 2. Data of the case study

City Name	Criterion Alternatives ID	Pharmacies	Dentist	Paramedic	Specialist and Subspecialty physician	General Practitioner	Active beds	laboratories	Primary medical care centers
Urmia	A_1	178	57	3578	278	159	2395	82	345
Oshnavieh	A_2	8	4	232	14	12	71	5	38
Bukan	A_3	29	10	792	38	23	256	10	97
Poldasht	A_4	3	3	164	10	10	38	4	40
Piranshahr	A_5	17	3	383	22	17	107	5	63
Tekab	A_6	7	4	387	17	23	96	6	56
Chaldoran	A_7	6	2	171	7	14	49	3	49
Chaypareh	A_8	6	4	136	10	11	56	4	23
Khoy	A_9	38	16	983	77	76	533	12	146
Sardasht	A_{10}	10	3	399	21	29	133	7	81
Salmas	A_{11}	15	7	558	29	41	191	8	96
Shahin Dezh	A_{12}	9	5	405	13	21	107	8	64
Showt	A_{13}	6	3	189	8	9	42	6	39
Maku	A_{14}	10	7	397	33	21	167	9	47
Mahabad	A_{15}	30	8	781	49	34	295	10	103
Miandoab	A_{16}	26	12	906	49	48	355	14	143
Naqadeh	A_{17}	17	4	468	37	27	182	9	59

Table 3. Weight of criteria

Primary medical care centers	Laboratories	Active beds	General Practitioner	Specialist and Subspecialty physician	Paramedic	Dentist	Pharmacies	Criterion
0.101	0.131	0.138	0.114	0.130	0.121	0.128	0.134	Weights

Table 4. Results of the TOPSIS Technique based on rank, cities, and relative size close to the ideal solution

C_i	City	Rank
1	A_1	1
0.12121	A_9	2
0.059369	A_{16}	3
0.02996	A_{15}	4
0.026448	A_3	5
0.018882	A_{11}	6
0.0091103	A_{17}	7
0.0078234	A_{10}	8
0.0065895	A_{14}	9
0.0051798	A_{12}	10
0.0040796	A_5	11
0.003719	A_6	12
0.00086423	A_2	13
0.00083071	A_7	14
0.00059851	A_{13}	15
0.00038084	A_4	16
0.00028289	A_8	17

Table 5. Results of TOPSIS's rankings

City	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}
Rank	1	13	5	16	11	12	14	17	2	8	6	10	15	9	4	3	7

Result of MOORA Technique

The MOORA calculation is made in Section 1.1. The weight of the criteria is shown in Table 6. In this method, the optimization score *(Y)* is calculated, and finally, the rank of alternatives is obtained. As indicated in Table 6, URMIA reached the maximum scores.

Table 6. Results of MOORA's rankings

City	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}
Rank	1	13	5	16	11	12	15	17	2	9	6	10	14	8	4	3	7

Result of the ARAS Technique

In this method, the value of the optimality function *(S)* and the utility degree *(K)* are determined based on the ARAS method explained in Section 3.3 and the weight of criteria indicated in Table 3.

Table 7. Results of ARAS's rankings

City	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}
Rank	1	13	5	17	11	12	15	16	2	9	6	10	14	8	4	3	7

Result of COPRAS Technique

In the current case, based on Section 3.4 and Table 3 the minimizing index value *(R)*, maximizing index value *(P)*, and relative significance value *(Q)* are calculated. The complete ranking of cities is shown in Table 8.

Table 8. Results of COPRAS's rankings

City	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}
Rank	1	13	5	17	11	12	15	16	2	9	6	10	14	8	4	3	7

According to the preliminary data, it can be seen that in many criteria, the city of Urmia is very different from other cities, and cities such as Khoy, Miandoab, and Mahabad are in a better situation than other cities. Based on the results of ranking techniques in Table 9, the first three cities are identical in all techniques used. Moreover, looking at these data, it can be seen that cities such as Poldasht, Chaldoran, and Chaypareh are not in a favorable situation. In this step, we use the Spearman rank correlation coefficient to calculate the relationship between the techniques used. Spearman rank correlation coefficient is a form of the Pearson correlation coefficient and measures the similarity between two ranking sets. The larger the number obtained, regardless of the sign, the greater the correlation between positive and negative signs. It indicates only the direction of solidarity.

Table 9. The ranking results of four MCDM methods

CITY	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}
TOPSIS	1	13	5	16	11	12	14	17	2	8	6	10	15	9	4	3	7
MOORA	1	13	5	16	11	12	15	17	2	9	6	10	14	8	4	3	7
ARAS	1	13	5	17	11	12	15	16	2	9	6	10	14	8	4	3	7
COPRAS	1	13	5	17	11	12	15	16	2	9	6	10	14	8	4	3	7

The following formula is used to calculate the Spearman correlation coefficient:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{20}$$

where d is the difference between the rank of the alternatives in the two methods and n is the number of alternatives. We used SPSS26 to calculate the Spearman correlation coefficient. Table 10 presents the results of a Spearman correlation experiment for four MCDM methods:

TOPSIS, MOORA, ARAS, and COPRAS. Key items in Table 10 include the correlation coefficients and significance values (Sig). The correlation coefficient measures the strength and direction of the association between the two methods' rankings, with values closer to 1 indicating a strong positive correlation. The significance value (Sig) indicates whether the correlation is statistically significant, with values close to 0 suggesting strong evidence that the correlation is not due to random chance.

The results reveal a very high degree of agreement between the rankings produced by each method. For instance, the correlation coefficient between TOPSIS and MOORA is 0.995, suggesting that these two methods produce almost identical rankings. Similarly, the correlation coefficients between TOPSIS and ARAS, as well as between TOPSIS and COPRAS, are 0.993 and 1, respectively, indicating an exceptionally high level of consistency.

MOORA also shows perfect correlations with COPRAS and ARAS and a coefficient of 0.998 with TOPSIS. These results underscore the reliability and interchangeability of these MCDM methods, as they consistently produce similar rankings for the same data set. Overall, the high correlations among TOPSIS, MOORA, ARAS, and COPRAS confirm their robustness and reliability in multi-criteria decision-making processes.

Despite the strong correlation between the four methods, some results still have minor differences. Inconsistencies arise when the number of alternatives increases or when their performance is similar, leading to concerns about the validity and reliability of the findings. Despite extensive efforts in developing MCDM models, there is no comprehensive or inherently superior approach for multi-criteria analysis. Since the results show that different MCDM methods produce varying outcomes when ranking alternative decisions with multiple criteria, we use the utility interval aggregation method to help decision-makers decide better.

Table 10. Spearman correlation coefficient

Methods	**Spearman Results**	**TOPSIS**	**MOORA**	**ARAS**	**COPRAS**
TOPSIS	Correlation Coefficient	1	0.995	0.993	0.993
	Sig	-	0	0	0
MOORA	Correlation Coefficient	0.995	1	0.998	0.998
	Sig	٠	-	0	0
ARAS	Correlation Coefficient	0.993	0.998	1	1
	Sig	0	0	-	-
COPRAS	Correlation Coefficient	0.993	0.998	1	1
	Sig	0	0	-	-
SUM	-	3.990	3.990	3.990	3.980
Weight	-	0.250	0.250	0.250	0.249

The proposed aggregation model is aimed at assisting managers in making robust decisions when ranking research centers (Bahadori et al., 2012). In this study, a linear programming (LP) model is initially developed to estimate the interval for each alternative, which in this case refers to cities. The LP model needs to be solved for each ranking method, denoted as $i = 1,\ldots,m$, using equations (32) to (35).

$$min/\max \quad u_{i1} \tag{32}$$

Subject to

$$u_{ij} - u_{i(j+1)} \geq \varepsilon_{j(j+1)} \qquad j = 1,2,\ldots,n-1 \tag{33}$$

$$\sum_{j=1}^{n} u_{ij} = 1 \tag{34}$$

$$u_{ij} \geq 0 \qquad j = 1,2,\ldots,n \tag{35}$$

in the given context, u_{ij} represents the utility perceived by the i^{th} ranking method for the j^{th} ranked alternative. Equation (32) represents the objective function, which calculates the minimum (u_{ij}^L) and maximum (u_{ij}^U) interval numbers for the first ranked alternative by each ranking method. The objective is to minimize this function. Equation (33) demonstrates the preference for alternative j over alternative $j+1$ in the i^{th} ranking method. It is formulated to minimize the difference, taking into account a small positive number denoted as ε. Equation (34) presents the normalized utility vector, which is derived as part of the analysis.

In our study, the number of alternatives *(i)* and the number of ranking methods *(j)* equal 17 and 4, respectively. It is assumed that the amount of ε is ranged as follows:

$$0 \le \varepsilon \le \varepsilon_{max} = 1/(n(n-1)/2) \qquad j = 1,2,\dots,n \tag{36}$$

According to Equation (36), ε_{max}=1/136, (n=17), and two evaluation sets are implemented for ε=0, 0.0073. All generated utility estimates from the rankings are provided in Table 11. The aggregated utility (weighted average utility) of each alternative (cities) can be calculated using the following formula:

$$u_j^L = \sum_{i=1}^{m} w_i u_{ij}^L \qquad j = 1,\dots,n. \tag{37}$$

$$u_j^U = \sum_{i=1}^{m} w_i u_{ij}^U \qquad j = 1,\dots,n. \tag{38}$$

The text outlines a method for assigning relative weights to ranking methods in an analysis. The weights are computed using a correlation matrix that shows the relationships between the ranking methods in Table 12. The matrix is normalized to ensure the weights reflect the methods' importance. The normalized sums of correlations are used as weights in equations (37) and (38) for further analysis. Table 12 summarizes the weighted average utility intervals of the case being studied for various values of ε. In the results presented in Table 9, we observed that in rankings of 8, 9, 14, 15, 16, and 17, there are differences in cities A_{10} and A_{14}, A_{13} and A_7, and A_4 and A_8. According to ranking obtained from the utility interval method and results in Table 13, it is concluded that A_{14} is superior to A_{10}, A_{13} is superior to A_7 and A_4 is superior to A_8.

Considering the allocation of health services in each city, as shown in Table 2, it can be seen that there is a huge difference in access to health services between Urmia, which is the capital of the province, and other cities, and therefore, cities such as Urmia, Khoy, Mahabad, and Miandoab are in a better situation than other cities. Also, cities such as Poldasht, Chaldoran, and Chaypareh have relatively lower conditions regarding health services. In addition, there is a big difference between larger cities such as Khoy, Mahabad, and Miandoab with smaller cities. However, it should be noted that the availability of health services in cities may be due to the population of cities. According to the health index, people's health and life expectancy are important in determining HDI. Cities can be divided into developed, developing, or underdeveloped cities. It should be noted that the distribution of health services in small and large cities is different.

Conclusion and further work

The Human Development Index (HDI) is a summary of the average achievements in the main dimensions of human development of a long and healthy life with appropriate knowledge and standard of living. Given the importance of people's health in determining HDI, access to health services is an important factor in people's health because, with proper allocation of health services in cities, the possibility of disease prevention and early treatment increases and due to the relationship between life expectancy which is one of the main indicators for calculation of HDI- and the health status of people, the amount of life expectancy and consequently HDI increases. Since the Human Development Index reflects the root causes of health inequalities within and between countries, it is important to evaluate this factor. Indicators of developing healthcare facilities and resources in developing countries do not have a fair and balanced distribution in different geographical areas.

Table 11. Utility interval estimates corresponding to the preference ranking of MCDM methods

Cities	$\varepsilon = 0$				$\varepsilon = 0.0073$			
	TOPSIS	**MOORA**	**ARAS**	**COPRAS**	**TOPSIS**	**MOORA**	**ARAS**	**COPRAS**
A_1	[0.0588,1]	[0.0588,1]	[0.0588,1]	[0.0588,1]	[0.1172, 0.124]	[0.1172, 0.124]	[0.1172,0.124]	[0.1172, 0.124]
A_2	[0,0.0769]	[0,0.0769]	[0,0.0769]	[0,0.0769]	[0.292, 0.298]	[0.292, 0.298]	[0.292, 0.298]	[0.292, 0.298]
A_3	[0,0.2]	[0,0.2]	[0,0.2]	[0,0.2]	[0.0876,0.0890]	[0.0876,0.0890]	[0.0876,0.0890]	[0.0876,0.0890]
A_4	[0,0.06]	[0,0.06]	[0,0.06]	[0,0.06]	[0.073,0.078]	[0.073,0.078]	[0,0.004]	[0,0.004]
A_5	[0,0.091]	[0,0.09]	[0,0.09]	[0,0.09]	[0.0438,0.044]	[0.0438,0.044]	[0.0438,0.0445]	[0.0438,0.0445]
A_6	[0,0.0833]	[0,0.0833]	[0,0.0833]	[0,0.0833]	[0.036,0.0371]	[0.036,0.0371]	[0.036,0.0371]	[0.036,0.0371]
A_7	[0,0.0714]	[0,0.0714]	[0,0.0714]	[0,0.0714]	[0.021,0.022]	[0.021,0.022]	[0.021,0.022]	[0.021,0.022]
A_8	[0,0.0588]	[0,0.0588]	[0,0.0588]	[0,0.0588]	[0,0.004]	[0,0.004]	[0.0073,0.078]	[0.0073,0.078]
A_9	[0,0.5]	[0,0.5]	[0,0.5]	[0,0.5]	[0.109,0.1131]	[0.109,0.1131]	[0.109,0.1131]	[0.109,0.1131]
A_{10}	[0,0.1250]	[0,0.111]	[0,0.111]	[0,0.111]	[0.0657,0.066]	[0.0584,0.059]	[0.0584,0.059]	[0.0584,0.059]
A_{11}	[0,0.1667]	[0,0.1667]	[0,0.1667]	[0,0.1667]	[0.0803,0.082]	[0.0803,0.082]	[0.0803,0.082]	[0.0803,0.082]
A_{12}	[0,0.1]	[0,0.1]	[0,0.1]	[0,0.1]	[0.051,0.0518]	[0.051,0.0518]	[0.051,0.0518]	[0.051,0.0518]
A_{13}	[0,0.0667]	[0,0.0714,]	[0,0.0714,]	[0,0.0714,]	[0.0146,0.015]	[0.0219,0.022]	[0.0219,0.022]	[0.0219,0.022]
A_{14}	[0,1]	[0,0.125]	[0,0.125]	[0,0.125]	[0.0584,0.059]	[0.0657,0.066]	[0.0657,0.066]	[0.0657,0.066]
A_{15}	[0,0.25]	[0,0.25	[0,0.25	[0,0.25	[0.095,0.0967]	[0.095,0.0967]	[0.095,0.0967]	[0.095,0.0967]
A_{16}	[0,0.333]	[0,0.333]	[0,0.333]	[0,0.333]	[0.1022,0.1046]	[0.1022,0.1046]	[0.1022,0.1046]	[0.1022,0.1046]
A_{17}	[0,0.1429]	[0,0.1429]	[0,0.1429]	[0,0.1429]	[0.073,0.074]	[0.073,0.074]	[0.073,0.074]	[0.073,0.074]

Table 12. The weighted average utility interval for ε=0 and ε=0.0073

Cities	$\varepsilon = 0$	$\varepsilon = 0.0073$
A_1	[0.0588,1]	[0.1172,0.124]
A_2	[0,0.07769]	[0.0292,0.03]
A_3	[0,0.2]	[0.0876,0.089]
A_4	[0,0.0606]	[0.0036,0.004]
A_5	[0,0.09091]	[0.0438,0.044]
A_6	[0,0.0833]	[0.0365,0.003]
A_7	[0,0.06785]	[0.01642,0.01]
A_8	[0,0.06066]	[0.0036,0.004]
A_9	[0,0.5]	[0.1095,0.113]
A_{10}	[0,0.1146]	[0.06022,0.06]
A_{11}	[0,0.1667]	[0.0803,0.081]
A_{12}	[0,0.1]	[0.0511,0.051]
A_{13}	[0,0.0702]	[0.02,0.02058]
A_{14}	[0,0.1215]	[0.0638,0.064]
A_{15}	[0,0.25]	[0.0949,0.096]
A_{16}	[0,0.33]	[0.1022,0.104]
A_{17}	[0,0.1429]	[0.073,0.0740]

Table 13. The aggregated rankings corresponding to Table 12

ε	Ranking
$\varepsilon = 0$	$A_1 \overset{0.6983}{\succ} A_9 \overset{0.60002}{\succ} A_{16} \overset{0.5714}{\succ} A_{15} \overset{0.555}{\succ} A_3 \overset{0.5454}{\succ} A_{11} \overset{0.5384}{\succ} A_{17} \overset{0.5404}{\succ} A_{14} \overset{0.5146}{\succ} A_{10} \overset{0.534}{\succ} A_{12} \overset{0.5238}{\succ} A_5 \overset{0.5217}{\succ} A_6 \overset{0.52}{\succ} A_2 \overset{0.74}{\succ}$ $A_{13} \overset{0.5086}{\succ} A_7 \overset{0.5279}{\succ} A_4 \overset{0.5}{\succ} A_8$
$\varepsilon = 0.0073$	$A_1 \overset{1}{\succ} A_9 \overset{1}{\succ} A_{16} \overset{1}{\succ} A_{15} \overset{1}{\succ} A_3 \overset{1}{\succ} A_{11} \overset{1}{\succ} A_{17} \overset{1}{\succ} A_{14} \overset{1}{\succ} A_{10} \overset{1}{\succ} A_{12} \overset{1}{\succ} A_5 \overset{1}{\succ} A_6 \overset{1}{\succ} A_2 \overset{1}{\succ} A_{13} \overset{1}{\succ} A_7 \overset{1}{\succ} A_4 \overset{1}{\succ} A_8$

In the present study, to evaluate the health status of West Azerbaijan province in Iran, eight criteria and 17 cities (alternatives) are determined. Criteria weights are calculated with the Shannon Entropy method, and cities are ranked by TOPSIS, MOORA, ARAS, and COPRAS techniques. According to the results, there are significant disparities among the cities of West Azerbaijan Province related to the allocation of health services, and the Spearman correlation coefficient between the results of the ranking method illustrates the high degree of correlation between them. The cities of Urmia, Khoy, and Miandoab are the first in terms of health services. This research employs four ranking methods, each offering distinct information on the degrees of preference. However, a combination method is necessary for accurate and final preferences.

The utility interval aggregation method in multi-criteria decision-making bridges this gap and improves the reliability of performance evaluation and ranking results. This approach aims to enhance the reliability of the final rankings and fill the void left by individual ranking methods.

In recent years, studies have shown inequalities in the allocation of health services in other provinces of Iran. In a study that classified the structural indicators of health in Golestan province, the results showed inequalities in the health sector between the cities of the province (Bahadori et al., 2012). In a similar study, the results showed a significant difference between cities in Kerman province in terms of access to health services (Anjomshoa et al., 2013). Therefore, based on our research and other mentioned studies, urban areas should focus on coordinated development to address barriers to healthcare development, while rural areas should address healthcare concerns based on local needs and circumstances. We conclude from this study that to achieve a fair and balanced healthcare status in different provinces based on their development status, programs should be set to reduce the distance to access health centers. Equitable and optimal distribution of health services and equal access must be the goal of all governments and health systems. The gap between cities in the allocation of health services should be minimized. In order to address the gap between the urban and rural areas of the province with regard to the equitable distribution of health services, it is necessary to develop a comprehensive and coordinated plan. This plan should move away from large-scale, centralized, and top-down planning approaches and instead focus on micro-local planning within smaller-scale geographic areas. For cities such as Poldasht, Chaldoran, and Chaypareh, which are clearly in a bad situation, short-term plans, and for other cities that are in a better position, medium-term plans can be a good idea. Policymakers need to address these gaps in the allocation of health facilities and plan to reduce access to health facilities to reduce the gap between access to health care and equitable distribution of these services. This inequality can lead to differences in the health status of people in different regions, so measures must be taken to address this problem and the lack of health services. One of the limitations of this study is the lack of access to life expectancy data by cities to calculate this index. If these data were available, it would be possible to examine the relationship between life expectancy in cities and the status of those cities in terms of indicators.

According to the foregoing results, the following suggestions are summarized for further research:

- Other MCDM techniques could be developed to solve the same problem and to compare with the proposed approach.
- In most real environments, criteria and their constraints are not deterministic and cannot be specified precisely; therefore, those criteria are uncertain or fuzzy and use MCDM techniques under a fuzzy environment.

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