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Hospital Facility Location Selection Using Permanent Analytics Process

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***Abstract*—**In this paper, a new MCDMA approach, the permanent analytics process is proposed to assess the immovable valuation criteria and their significance in the placement of the healthcare facility. Five decision factors are considered for the value and selection of immovables. In the multiple factor selection problems, the priority vector of the criteria used to compare several immovables is first determined using the permanent analytics method, a mathematical model for the multiple criteria decision-making process. Then, to demonstrate the viability and efficacy of the suggested approach, twenty potential candidate locations were evaluated using the hospital site selection problem's decision criteria. The ranking accuracy of estimation was evaluated using composite programming, which took into account both the permanent analytics process and the weighted multiplicative model.

***Keywords*—**Hospital Facility Location Selection, Permanent Analytics Process, Multiple Criteria Decision Making (MCDM).

I. Introduction

The hospital facility location problem is a critical decision-making process for institutions and organizations considering investing in healthcare facility installation. Hospital facility location selection can be viewed as an immovable valuation problem. Therefore, an immovable valuation model and real estate valuation process are proposed to solve the problem under consideration.

The key elements of the immovable valuation are described to demonstrate how the selection problem is conceptualized theoretically. Immovable is an entity that cannot move from one place to another, it is the name given to properties in agricultural, residential, and industrial classes that cannot be moved from one place to another without harming the essence of an asset. Immovable property has legal property rights attached to it. The concept of immovable valuation is determining the value of immovable by considering multiple characteristics. Immovable valuation is the computational process of determining the value of an immovable at the time of purchase, considering factors such as its quality, benefit, and environmental conditions of use.

Demand for immovable is increasing due to increasing population pressure and an attractive asset as an economic investment tool. In the real estate industry, the valuation process determines the value of immovable which affects the level of various taxes, including property and income taxes. Within the scope of immovable valuation; agricultural, residential, health, and industrial applications; immovable taxation, expropriation, privatization, land consolidation, free market trading value, banking transactions, land, and land arrangement. Immovable valuation is the determination of absolute values by analyzing characteristic attributes and statistics of immovables.

Conversely, a decision support system can be used in the immovable valuation process. The decision support system has a database where the data is recorded and an algorithm that runs this data. With each new data and information added to this system, the algorithm directly analyzes and classifies the data without taking on a complex structure.

In addition to the modern data analytics systems, various classical methods such as market, income, and cost approaches are used when valuing immovables. Determining the value of immovable is a complex process. The reason for this is that there is no law, regulation, or similar legal regulation regarding the issues to be considered in the immovable valuation process and all experts use no strictly applicable method. Therefore, it is difficult to make an objective immovable assessment.

Contrarily, there are a number of factors that make it challenging to estimate the value of an immovable, including the challenge of locating an immovable that can be regarded as equivalent to the immovable whose value is to be evaluated, the existence of multiple factors affecting the price, and the variability of these factors according to regions. Technical, economic, and sociological problems arise because immovable cannot be evaluated realistically in many applications, from immovable tax to appropriation, from privatization to land and land arrangement. Therefore, valuators should do immovable valuations objectively. The valuators can achieve this by basing the immovable valuation on permanent analytics process.

The immovable valuation process can use subjective and objective methods of immovable valuation. Although a subjective method is utilized to value immovable property, no methodological evaluation system is employed.

The evaluators who appraise an immovable object decide its worth under the subjective valuation approach. The subjective attitudes and actions of valuers also have an impact on immovable valuation. In this subjective method, the value of an immovable is determined by how rare or useful it is to an individual.

While the objective methods perform the valuation of the immovable, the multiple criteria decision analysis methods that consider the attributes/criteria that are effective on the value of the immovable and their degree of importance are applied.

However, because each immovable is unique in terms of its location and intended use, people have varying

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expectations for the amount and caliber of these properties. Therefore, it is impossible to ascertain an immovable's actual worth.

The criteria used in the valuation of immovable and which of these criteria are more important are not known. An immovable valuation can more precisely reflect real market worth by applying permanent analytics process. Valuers must show comprehensibility, prudence in their assumptions, and clear and appropriate identification of comparable properties utilized as a value comparison during the immovable valuation process.

Decision-making is making choices by determining a decision, gathering information, and evaluating alternative solutions. Using an algorithmic decision-making process can help make more informed, rational, and thoughtful decisions by organizing relevant information and identifying alternatives. This mathematical approach increases the chances of choosing the most satisfactory alternative possible [1,2].

Decision-making is selecting one or more of the most appropriate possible options from a set of options, usually based on at least one goal and criterion. In order to make the most precise decision with regard to numerical data, multiple criteria decision-making analysis (MCDMA) approaches, which are based on pairwise comparisons of the criteria specified to make the correct conclusion in the decision-making process, are used [3].

The decision-making problem of immovable valuation can also be solved using MCDMA techniques. MCDMA techniques differ from one another in various positive and negative ways. Deciding which approach works best is important before beginning a problem-solving project. The decision maker should consider both the process' characteristics and the problem's nature while choosing the best method. [4, 5].

Using MCDM techniques is intended to determine the relative weights of the immovable valuation factors. The permanent analytics process is suggested in order to determine the levels of significance of the criteria. A decision hierarchy and an integer comparison scale are used to pairwise compare the criteria influencing the decision regarding relevance values. The goal, criteria / sub-criteria, and options are the different hierarchical levels at which the decision problem might be organized using the suggested method.

Twenty potential movables were looked at as part of the process of choosing a hospital location when the proposed technique was applied. The five fundamental decision criteria for the land area were location, zoning, population, environmental, and transportation status.

The study's road map is given as follows; a unique MCDM method is introduced in the second chapter, which discusses permanent analytics process. Also explained is the composite programming technique. The third chapter uses composite programming to evaluate a problem application with permanent analytics process. The investigation is analyzed, and the findings are explained in the fourth chapter.

II. METHODOLOGY

Decision-makers in the immovable valuation process must weigh a variety of factors while deciding between the options they are presented with. Making a quantitative decision after evaluating the options requires considering each option and the expected outcomes. The basic goal of decision-making is to select the best alternative among the alternatives as a consequence of this computational valuation procedure.

The Decision-making process includes decision makers, alternatives, criteria, priorities of the decision-makers, and the results of the decision. A decision problem arises when there are at least two alternatives in the decision-making process. The decision-making process can be completed by decision-makers choosing one of the alternatives or ranking the alternatives quantitatively [6].

The proposed MCDMA technique includes an analytical selection process that gives the best choice within the criteria and purpose based on evaluation criteria and pairwise comparison among the alternatives. There are many MCDMA methods used in the decision-making process and among these, the most frequently used multiple criteria analysis methods were identified as MAUT [7,8,9], AHP [10,11,12,13], TOPSIS [14,15,16], VIKOR [17,18,19], ELECTRE [20,21,22], PROMETHEE [23,24,25,26], and ORESTE [27,28,29]. Here, multiple criteria decision analysis based on permanent analytics process, which is suitable for the nature of the immovable valuation decision problem, is proposed as a new MCDMA technique.

Decision-making methods can be classified into two general categories; utility determining methods (multiple attribute utility techniques, compensatory methods, or performance aggregation-based methods) (MAUT, AHP, TOPSIS, VIKOR) and outranking methods (partially compensatory or preference aggregation-based methods) (ELECTRE, PROMETHEE, ORESTE) [2, 3, 31].

A sophisticated capability that can resolve the decision dilemma during the decision-making process is the capacity to make the proper choice. However, decision-makers often have difficulty choosing the best option, as they may not fully understand their preferences or lack a systematic approach to solving the decision-making problems.

The permanent analytics process technique can transform the interrelations between factors into an understandable structural model of the hierarchical analytical system. Therefore, it is a viable and valuable tool for analyzing the interdependent relationships among elements in a complex system and ranking them to indicate complex multiple criteria decision-making.

The permanent analytics process provides a mathematical model that helps decision makers arrive at the most logical choice based on their preferences. The permanent analytics process combines qualitative and quantitative analysis of the multiple criteria decision analysis approach. The permanent analytics process is essentially based on three principles: decomposition, measurement of preferences, and synthesis. This approach divides the decision problem into objectives, criteria, and alternatives from a qualitative point of view and calculates the quantitative hierarchy importance weight with the relationships among the holistic structure of these factors, evaluates the relative importance of the various elements, and then quantifies the decision [32].

To address issues with decision-making, permanent analytics process is built as a mathematical model. Permanent analytics process has a simple hierarchical and analytical process to make complex decision-making problems easy and solvable. This technique has a broad range of applications and can be used to practically any decision-making process. The most important feature of the permanent analytics process is that the decision-maker can include both objective and subjective thoughts in the decision process.

Permanent analytics process is a mathematical decision-making model with a wide application area, in which decision-making groups share their ideas to solve problems, and in which goals and alternatives are analyzed to achieve the best result in line with the purpose. Direct pairwise comparison matrices represent evaluators' preferences in decision-making processes. In MCDMA problems, different mathematical methods are applied to obtain processed information from these decision matrices. In AHP [10,11,12,13,33,34,35,36,37,38] method, a hierarchy weighs how a goal is distributed among the elements under comparison and determines which element has a stronger impact on that goal. Although the AHP can be used to rank alternatives and establish the weights of the criteria, it assumes that the criteria are independent and ignores their interconnections and interactions. The ANP, a more sophisticated form of the AHP, can handle the reliance and feedback between criteria, the assumption of equal weight for each cluster to generate a weighted supermatrix in the ANP is not sensible in real-life circumstances [46,47,48].

The fundamental principle of TOPSIS is that the selected alternative should be the closest to the ideal solution and the furthest away from the negative ideal solution [14]. The VIKOR approach uses linear normalization to establish a ranking index based on a specific measure of "closeness" to the ideal solution [17]. The ELECTRE is an outranking MCDMA technique that uses multiple attribute utility theory to choose the best action from a list of possible alternatives [20]. In multiple criteria decision-making situations, the PROMETHEE is a major method for assessing options regarding criteria. It is distinguished by a wide variety of preference functions, which are applied to allocate the differences between alternatives in judgments [23]. The ORESTE method's algorithm determines a global preference structure for a set of options by assessing each one according to its preference for each criterion. This method sets criteria and alternatives broadly, then uses indifference and conflict analysis to build the global full and partial preorder of alternatives [27].

The DEMATEL technique [39,40,41 efficiently examines the mutual influences (direct and indirect effects) among various components and comprehends the complex cause and effect relationships in the problem of decision-making. The decision maker can clearly comprehend which factors have mutual influences on one another due to its ability to visualize the interrelationships between factors using an influential relation map. It can be used to rank alternatives as well as identify important assessment criteria and gauge the relative importance of different evaluation criteria.

The Graph Theory and Matrix Approach (GTMA) method [42,43,44,45] is based on pairwise comparisons and a graph structure, like AHP and ANP, however unlike AHP, decision-makers are not required to assess whether characteristics are dependent. The total number of pairwise comparisons when using GTMA is substantially fewer than when using ANP because it is of the same order as the AHP approach. Like the ANP, the GTMA technique considers alternatives as a component of the decision-making problem, although it does so in a less thorough manner than the AHP and the ANP. Permanent analytics process is a mathematical model that provides a hierarchical display of principal objectives, criteria, and sub-criteria in complex, multiple-criteria decision analysis problems.

According to the permanent analytics process, the objective must be established before a hierarchical structure is developed for it. The permanent analytics process can contribute to the decision makers' processes of structuring and analyzing decision problems in many different fields with great success in application. The essential procedural steps of permanent analytics process are presented as follows [10,39,45]:

Step 1. Generate the direct comparison matrix *X*. A direct comparison matrix $X = \left[x_{ij}\right]_{nxn}$ is established by the importance of *n*-factors $F = \{F_1, ..., F_n\}$ in a system. The direct pairwise comparison influence of factor F_i on factor F_j is evaluated by using an integer comparison scale (Table 1).

Table 1. Comparison scale for permanent analytics process

Importance	Description
0	No influence
1	Low influence
3	Moderate influence
5	High influence
7	Very high influence
9	Extreme influence
2,4,6,8	Intermediate values

Comparison matrix X , $X=\left[x_{ij}\right]_{nxn}$, consists of positive and inverse values $x_{jk}=1/x_{ij},\forall_{i,j}=1,...,n$.

$$X=\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix} \quad (1)$$

The individual direct comparison matrix $X^k=\left[x_{ij}^k\right]_{nxn}$ can be formed, where all principal diagonal elements are equal to zero, and $\left[x_{ij}^k\right]$ represents the decision maker's judgment E_k on the degree of factor F_i affects F_j. By aggregating the *I* experts' opinions, the group direct comparison matrix $X=\left[x_{ij}\right]_{nxn}$ can be obtained by

$$x_{ij}=\frac{1}{I}\sum_{k=1}^{I}x_{ij}^k \;, i,j=1,...,n \quad (2)$$

Step 2. Establish the normalized direct comparison matrix *Z*. When the group direct comparison matrix *X* is obtained, the normalized direct comparison matrix $Z=\left[z_{ij}\right]_{nxn}$ is acquired by

$$Z=\frac{X}{s}\,,\, s=\max\left(\max_{1\le i\le n}\sum_{j=1}^{n}x_{ij},\; \max_{1\le j\le n}\sum_{i=1}^{n}x_{ij}\right) \quad (3)$$

All elements in the matrix *Z* are complying with the $0\le z_{ij}\le 1$, $0\le\sum_{j=1}^{n}z_{ij}\le 1$, and least one i such that $\sum_{j=1}^{n}z_{ij}\le s$.

Step 3. Construct the total comparison matrix *T*. Using the normalized direct comparison matrix *Z*, the total comparison matrix $T=\left[t_{ij}\right]_{nxn}$ is then computed by summing the direct impacts and all the indirect impacts by

$$T=Z+Z^2+Z^3+...+Z^u=Z(I-Z)^{-1} \quad (4)$$

when $u\to\infty$, in which *I* is denoted as an identity matrix.

Step 4. Compute the sum of the rows R_i and the sum of the columns C_j from the total comparison matrix *T*. The vector R_i represents the priority status of the factors.

$$R_i=\left[r_i\right]_{nx1}=\left[\sum_{j=1}^{n}t_{ij}\right]_{nx1} \quad (5)$$

$$C_j=\left[c_j\right]_{1xn}=\left[\sum_{i=1}^{n}t_{ij}\right]_{1xn}^T \quad (6)$$

where r_i is the *i*th row sum in the total comparison matrix *T* and represents the sum of the direct and indirect impacts that flow from factor F_i to the other factors. Similar to that, c_j represents the sum of the direct and indirect impacts that factor F_j receives from the other factors and is represented by the *j*th column sum in the total comparison matrix *T*.

Let $i=j$, and $i,j\in\{1,..,n\}$, the dispatching r_i and receiving c_j influence flows are aggregated into the net influence flow

$$\varphi_i=r_i-c_i \quad (7)$$

where $\varphi_i\in[-1,1]$, $\sum_{i=1}^{n}\varphi_i=0$, and the vector $\varphi_i=r_i-c_i$ indicates the net effect that the factor contributes to the system. When $\varphi_i=r_i-c_i$ is positive, the factor F_i has a net influence on the other factors and can be categorized as a cause group; when $\varphi_i=r_i-c_i$ is negative, the factor F_i is influenced by the other factors as a whole and can be categorized as an effect group.

Step 5. The priority vector of factors is calculated.

$$q_i=\frac{r_i}{r_i+c_i} \quad (8)$$

$$\omega_i=\frac{q_i}{\sum_{=1}^{n}q_i},\; i=1,...,n \quad (9)$$

where $\omega_i\in[0,1]$ and $\sum_{i=1}^{n}\omega_i=1$. The permanent analytics process complete ranking is obtained by ordering the actions or factors according to the decreasing values of the net flow scores.

Step 6. Construct the permanent comparison matrix *H* using the direct comparison matrix *Z*. The principal diagonal elements $R_i^k=\left\{R_i^1,...,R_i^k\right\}$ of the permanent matrix are substituted by the attributes' values x_{ij}, $i\ne j$, expressing the relative priority between them.

$$H_i = \begin{pmatrix} R_i^1 & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & R_{ij}^k \end{pmatrix} \quad (10)$$

Step 7. Calculate the determinant of the total comparison matrix *T* of the permanent comparison matrix *H*, following the same procedure after constructing the permanent matrix *H*.

$$\pi_i^{\mu} = det(T_i) = |T_i| = |t_{ij}|_{nxn} \quad (11)$$

where π_i^{μ} gives the final total score of *i*th alternative according to all decision criteria. Finally, the alternatives are ranked in descending order. The alternative with the highest-ranking order can be considered the optimal solution.

Step 8. The weighted multiplicative model validates permanent analytics process.

$$\pi_i^{\nu} = \prod_{j=i}^{n} x_{ij}^{\omega_j} \ , \ i = 1,...,m; j = 1,...,n \quad (12)$$

where m denotes the number of alternatives and n denotes the number of criteria (attributes).

Step 9. Compute Spearman's rank-order correlation. Spearman's correlation coefficient (ρ_s) measures the strength and direction of relationship between two ranked variables. It is used to discover the power of a link between two sets of data.

$$\rho_s = 1 - \left(\frac{6\sum d_i^2}{n(n^2-1)} \right) \quad (13)$$

where ρ_s represents Spearman's correlation coefficient, *n* is the number of data pairs, and d_i^2 is the square of the difference between the two variables' ranks for each data set.

Step 10. Sensitivity analysis is performed by composite programming. The composite programming method seeks a common optimality criterion based on two optimality criteria. The first criterion of optimality is the permanent analytics process (π_i^{μ}).

The second criterion of optimality is the weighted multiplicative model (π_i^{ν}). To increase the ranking accuracy and efficiency of the decision-making process, a more generalized equation is developed to determine the total relative importance of the *i*th alternative in the composite method.

$$\pi_i = \lambda \pi_i^{\mu} + (1-\lambda)\pi_i^{\nu} \quad (14)$$

where $\lambda \in [0,1]$, π_i^{μ} denotes permanent analytics process, and π_i^{ν} denotes weighted multiplicative model. The feasible alternatives are ranked by their π_i value and the best alternative has the highest π_i value. The composite programming method turns into a weighted multiplicative model when the λ value is 0, and the permanent analytics process method when λ is 1. It is applied to solve the MCDMA problem to improve the sequencing accuracy and can achieve the highest prediction accuracy.

III. Application

This chapter presents the proposed model's results to the hospital facility location selection problem. The numerical example is based on relevant data, parameters, and comparisons. The evaluation committee uses a decision support system based on permanent analytics process to address the challenge of choosing the placement of the hospital facility. The evaluation committee has identified a list of criteria (attributes) and alternatives for the decision problem: Position status (C1), Zoning status (C2), Population status (C3), Environmental status (C4), and Transportation status (C5).

Permanent analytics process examines the determined immovable valuation criteria of the hospital facility location problem due to the nature of the criteria and the uncertainty associated with the criteria. With a mathematical structure that ignores the interdependence of criteria and feedback, permanent analytics process is a robust method that considers the relationships between factors and alternatives and makes an appropriate decision.

A decision method should make the appropriate calculations capable of addressing the complexity of the problem. Therefore, the permanent analytics process was considered to generate an acceptable selection solution. The method theoretically defines matrix structures and evaluations that practitioners can easily understand. The evaluation committee established decision criteria that evaluated the same aspect of decision-making and were also independent of each other (see Table 2).

Table 2. Immovable valuation factors

Factors	Description
Position status (C1)	The width of the land's frontage to the road, the transportation distance, the landscape, and the urban development situation
Zoning status (C2)	The smooth geometry of the land and the elevation difference due to its slope. The size, height, type, and precedent value of the building that can be built
Population status (C3)	The population density around the land and the quality of the demographic characteristics of the population

Environmental status (C4)	The land's social and technical infrastructure and equipment contribute to urban life. The quality of the factors affecting the environmental and socioeconomic status of the land
Transportation status (C5)	The transportation facilities around the land, the existing access roads, and the quality of the transportation types

The identified decision criteria are then assumed to be independent of each other, and feedback between the factors and alternatives is ignored. Based on these assumptions, it is possible to define a three-level hierarchical structure and use the permanent analytics process (Fig.1). The hierarchy of the permanent analytics process model decomposes the evaluation process into the goal, factors/criteria, and alternatives. The proposed approach determines the most satisfying choice for the hospital facility selection problem.

To split the decision problem into a hierarchy including the most crucial components, a hierarchy of permanent analytics process should be developed after defining the characteristics and hierarchical structure of the choice problem and clearly stating the objectives and results. After that, a hierarchical framework containing decision-making elements is created from the complex problem (Fig. 1).

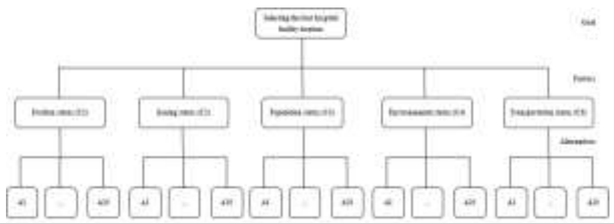

Fig.1 A representation of the hierarchy of the permanent analytics process model

In the application process, first, according to the integer comparison scale (Table 1) and the steps of the permanent analytics process model, the evaluation committee compares the defined criteria pairwise. Then, the weight vectors at the criteria levels are computed using Equations (1-9). The main diagonal elements of the direct comparison matrix X are given below, with zero values (Table 3).

Table 3. The direct comparison matrix X

	C1	C2	C3	C4	C5
C1	0	3	5	3	7
C2	1/3	0	3	7	5
C3	1/5	1/3	0	1	9
C4	1/3	1/7	1	0	7
C5	1/7	1/5	1/9	1/7	0

The normalized direct comparison matrix Z gives values $z_{ij} \in [0,1]$ (Table 4).

Table 4. The normalized direct comparison matrix Z

	C1	C2	C3	C4	C5
C1	0,0000	0,1071	0,1786	0,1071	0,2500
C2	0,0119	0,0000	0,1071	0,2500	0,1786
C3	0,0071	0,0119	0,0000	0,0357	0,3214
C4	0,0119	0,0051	0,0357	0,0000	0,2500
C5	0,0051	0,0071	0,0040	0,0051	0,0000

The total comparison matrix T is determined to obtain the vector of criterion weights. (Table 5).

Table 5. The total comparison matrix T

	C1	C2	C3	C4	C5
C1	0,0064	0,1136	0,1985	0,1452	0,3720
C2	0,0174	0,0067	0,1214	0,2593	0,2880
C3	0,0096	0,0157	0,0063	0,0426	0,3393
C4	0,0138	0,0090	0,0404	0,0065	0,2697
C5	0,0054	0,0079	0,0061	0,0079	0,0067

Finally, to obtain the vector of criterion weights, the values of R_i and C_i are computed from the total comparison matrix T (Table 6). The priority vector ω_i of criteria determines the ranking order of alternatives as $5 \prec 4 \prec 3 \prec 2 \prec 1$. After the pairwise comparison process, with a rate of 34%, the location status of immovable valuation was determined to be the element with the highest priority. Also, the priority vector of criteria result indicates the relative importance of the location status factor in evaluating the immovable property. Investing institutions or organizations should consider the importance of the location factor when making a mathematical decision.

Table 6. The priority vector of factors

	R_i	C_i	Q_i	ω_i	Rank
C1	0,8358	0,0525	0,9409	0,3439	1
C2	0,6928	0,1528	0,8193	0,2995	2
C3	0,4134	0,3727	0,5259	0,1922	3
C4	0,3394	0,4616	0,4237	0,1549	4
C5	0,0339	1,2756	0,0259	0,0095	5

A graphical representation of the priorities of the factor preferences in the decision problem is given (Fig.2).

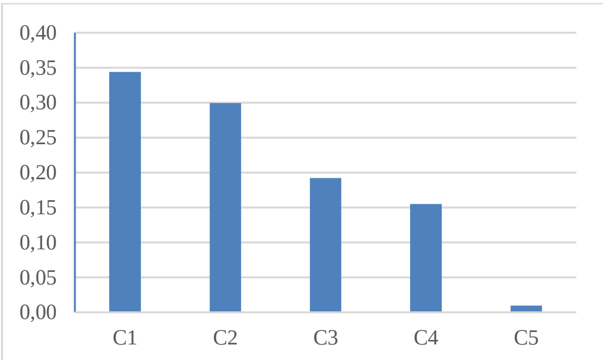

Fig. 2 A graphical representation of the priorities of factor preferences

Following the pairwise comparison of the factors, a number of alternatives ($A_i, i = 1...m$) (Table 7) - twenty hospital facility locations - were evaluated by the evaluation committee using the comparison scale (Table 1).

Table 7. Rating of alternatives according to factors

A_i	C1	C2	C3	C4	C5
A1	6	2	9	6	4
A2	9	5	9	2	8
A3	4	6	8	5	7
A4	5	4	6	3	3
A5	8	6	8	3	4
A6	4	8	9	2	7
A7	3	9	3	6	8
A8	6	9	9	9	5
A9	8	3	7	4	2
A10	4	3	5	6	7
A11	3	4	2	3	2
A12	9	4	2	3	9
A13	5	3	4	5	9
A14	6	9	2	5	5
A15	2	5	6	8	8
A16	3	8	6	8	4
A17	3	2	6	5	3
A18	9	9	5	5	6
A19	3	6	6	9	5
A20	7	9	2	9	6

Once the priorities of the factors are derived and the alternatives are rated, the next step is to determine the performance of the alternatives under the weights of the factors. At this stage, the main elements of the diagonal of the direct comparison matrix *X* (now referred to as the permanent comparison matrix) are replaced by elements of each vector of alternatives. Here, only the procedural steps of the first alternative (*A1*) are shown in the permanent comparison matrix so as not to take up much space. Due to this, only the procedural outcomes of the other possibilities are provided; the reader is left to take note of the intermediate procedural steps. However, the main elements of the diagonal of the direct comparison matrix *X* are replaced by the alternative vector (*A1*) (Table 8).

Table 8. The direct comparison matrix *X* of the permanent comparison matrix *H*

	C1	C2	C3	C4	C5
C1	**6**	3	5	3	7
C2	1/3	**2**	3	7	5
C3	1/5	1/3	**9**	1	9
C4	1/3	1/7	1	**6**	7
C5	1/7	1/5	1/9	1/7	**4**

The performance values of the first alternative (*A1*) based on the permanent comparison matrix *H* (Table 8) are given in the total comparison matrix *T* (Table 9).

Table 9. The total comparison matrix *T* of the permanent matrix *H* for the first alternative (*A1*)

	C1	C2	C3	C4	C5
C1	0,2398	0,1314	0,2973	0,1925	0,4771
C2	0,0206	0,0741	0,1592	0,2994	0,3230
C3	0,0145	0,0205	0,4022	0,0637	0,4739
C4	0,0183	0,0107	0,0609	0,2399	0,3361
C5	0,0066	0,0085	0,0085	0,0097	0,1512

By applying the equation (11) to the total comparison matrix *T*, the determinant process ($\pi_i^{\mu} = det(T_i)$) yields the final performance score for the alternative (*A1*) (Table 10). The final performance score of the option (*A1*) is $det(T_1) = 0,000176882$.

Table 10. Final ranking performance scores of alternatives using the permanent analytics process model

A_i	π_i^{μ}	Rank
A1	0,000176882	9
A2	0,000265657	8
A3	0,000290953	6
A4	0,000069831	17
A5	0,000338208	4
A6	0,000168577	10
A7	0,000129092	12
A8	0,001922161	1
A9	0,000128686	13
A10	0,000088520	15
A11	0,000008450	20
A12	0,000047267	18
A13	0,000070519	16
A14	0,000137255	11
A15	0,000126890	14
A16	0,000326122	5
A17	0,000031095	19
A18	0,000737618	2
A19	0,000284355	7
A20	0,000377514	3

The ranking pattern of the alternatives (Table 10) shows that option (*A8*) outperforms the other options, so that it may be an optimal choice for the hospital facility location problem.

The permanent analytics process model is then compared with the weighted multiplicative model to confirm its validity in decision-making. Following that, the weighted multiplicative model's assessment of alternative immovables is provided (Table 11). Also, the ranking pattern of the alternatives obtained from the weighted multiplicative model shows that alternative (*A8*) is ranked higher than the other alternatives. Accordingly, it may be an optimal choice for the hospital facility location problem.

Table 11. Final ranking performance scores of alternatives using the weighted multiplicative model

A_i	π_i^v	Rank
A1	0,045681267	13
A2	0,058672238	5
A3	0,052758245	6
A4	0,043752713	15
A5	0,061537709	3
A6	0,051038758	9
A7	0,046026521	12
A8	0,076484330	1
A9	0,050620918	10
A10	0,040287023	17
A11	0,029602994	20
A12	0,043815034	14
A13	0,040610480	16
A14	0,052297787	8
A15	0,040105804	18
A16	0,052727740	7
A17	0,032278778	19
A18	0,071825290	2
A19	0,049370120	11
A20	0,060506251	4

The MCDMA approach is a classification, ranking, and selection methodology widely used in decision-making problems. The degree of similarity between two or more orders is significant for interpreting comparisons. In that context, the degree of similarity of the rankings produced by the MCDMA methods for the same problem is essential.

Spearman's rank correlation coefficient, a widely used non-parametric measure of the rank correlation coefficient, shows the statistical dependence of ranking between two variables. In this study, the Spearman rho (ρ_s) similarity coefficient compares the rank order results of MCDMA methods.

The levels of correlation between the performance results of the weighted multiplicative model and the permanent analytics process model were evaluated. Therefore, the success of the MCDMA method, which consistently and significantly provides the highest correlation with the other method, can be evaluated as an indicator of ability or capacity.

The computed Spearman rho (ρ_s) similarity coefficient was significant for the statistical dependence of ranking between two variables produced by the two methods using the same data set for the same problem.

$$\rho_s = 1 - \left(\frac{6\sum d_i^2}{n(n^2-1)} \right) = 1 - \left(\frac{6(106)}{20(20^2-1)} \right) = 0,9203$$

By usual standards, Spearman’s coefficient of 0,9203 is close to 1, so one can say that the ranks are in solid agreement. The association between the two variables is considered statistically significant. Also, data reliability is related to the size of the data set. The more data there is, the more reliable the result.

Using the composite programming technique, the decision-making problem underwent sensitivity analysis. After comparing permanent analytics process and the weighted multiplicative model to ensure that the results are consistent, sensitivity analysis is carried out to evaluate the solution's robustness. Composite programming combines the two MCMDA methods by the parameter λ, which allows tracing for the stability of the ranking accuracy and efficiency of the decision-making process.

The λ parameter was changed in the range [0,1] to test the combined performance of the two MCDMA methods (Table 12 and Table 13).

Also, when the λ parameter takes a value of 0, the composite programming model reduces to the permanent analytics process model. When the λ parameter takes a value of 1, the composite programming model reduces to the weighted multiplicative model.

The weight of the maximum group benefit is indicated by the λ value. This λ value, which falls between 0 and 1, is typically considered to be 0.5. In composite programming, it is assumed that a result based on consensus among the solutions is obtained when λ= 0.5 [49].

The ranking order patterns in Table 13 indicate that the alternative (*A8*) gets the same first rank order (1) for all λ parameters. Therefore, it is chosen as the best hospital facility location. Other ranking order patterns showed slight signs of change when λ parameters were set, thus, demonstrating the effectiveness of the decision-making process and the proposed computational model's very consistent ranking accuracy.

IV. Conclusion

This study aims to make MCDMA-based recommendations and measure the performance of an appropriate and accurate immovable valuation process. Also, it is difficult to determine the most appropriate MCDMA method to use in a multiple criteria evaluation environment because many MCDMA methods suggest the best satisfactory alternative. However, the best (optimal) choice is often different depending on the MCDM method chosen under other circumstances.

Therefore, this complex situation represents uncertainty in the decision-making process. Also, it is difficult to recommend a suitable MCDMA selection procedure in this uncertain environment. Often, MCDMA method selection is affected by factors such as method capabilities, compatibility with the problem, familiarity, and software support.

In this context, a new MCDMA method - permanent analytics process - for hospital facility location selection is proposed. Data analytics method can rank many criteria in complex systems in order of priority by examining them according to the level of impact on each other. The criterion with the highest priority and the most impact is called the influencing criterion.

The permanent analytics method allows easy solutions to the problem by separating the seemingly difficult decision-making problems into degrees of importance. The data analytics method evaluates criterion weights objectively. The relationship between the immovable valuation criteria in the selection of the hospital facility location was systematically revealed and data

analytics method was applied to measure the immovable valuation performance of the alternatives.

The new MCDMA method with higher correlations is more suitable for real-life modeling problems. The more MCDMA result pattern contains a higher amount of information, the MCDMA method is more convenient and has better capacity. The computational methods used in multiple criteria decision-making analysis (MCDMA) assist the subjective assessment of a finite set of alternatives under a limited set of performance criteria by a single decision maker or a group of decision-makers. Making decisions involves selecting from a variety of alternatives.

The available alternatives can be ranked according to different performance criteria using computational approaches. Decision-makers assess how well each alternative performs against a set of criteria as well as the relative weight of the criteria to reach a final judgment. Decision-makers then consider the relative opinions of each group member as a group. Before an acceptable compromise solution materializes, each member of a group of decision-makers must also consider how to assess the quality and relative powers of the other members

Following the proposed procedural steps of permanent analytics process, essential MCDMA calculations were made in terms of five immovable criteria for twenty hospital facility location alternatives. Permanent analytics process and weighted multiplicative model were compared to validate the ranking patterns of the alternatives. Spearman's rank-order correlation analysis values confirm a significant coefficient of similarity between the two MCDMA methods.

Finally, sensitivity analysis performed with composite programming technique revealed relatively stable rank patterns of alternatives. Permanent analytics process can be recommended for applications in other research areas for classification, ranking, and selection problems.

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Table 12. Effect of λ on ranking accuracy of estimation and the efficiency of the decision-making process

λ	0	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	1
A1	0,045681	0,041131	0,000035	0,032030	0,027480	0,022929	0,018379	0,013828	0,009278	0,004727	0,000177
A2	0,058672	0,052832	0,000053	0,041150	0,035310	0,029469	0,023628	0,017788	0,011947	0,006106	0,000266
A3	0,052758	0,047512	0,000058	0,037018	0,031771	0,026525	0,021278	0,016031	0,010784	0,005538	0,000291
A4	0,043753	0,039384	0,000014	0,030648	0,026280	0,021911	0,017543	0,013175	0,008806	0,004438	0,000070
A5	0,061538	0,055418	0,000068	0,043178	0,037058	0,030938	0,024818	0,018698	0,012578	0,006458	0,000338
A6	0,051039	0,045952	0,000034	0,035778	0,030691	0,025604	0,020517	0,015430	0,010343	0,005256	0,000169
A7	0,046027	0,041437	0,000026	0,032257	0,027668	0,023078	0,018488	0,013898	0,009309	0,004719	0,000129
A8	0,076484	0,069028	0,000384	0,054116	0,046659	0,039203	0,031747	0,024291	0,016835	0,009378	0,001922
A9	0,050621	0,045572	0,000026	0,035473	0,030424	0,025375	0,020326	0,015276	0,010227	0,005178	0,000129
A10	0,040287	0,036267	0,000018	0,028227	0,024208	0,020188	0,016168	0,012148	0,008128	0,004108	0,000089
A11	0,029603	0,026644	0,000002	0,020725	0,017765	0,014806	0,011846	0,008887	0,005927	0,002968	0,000008
A12	0,043815	0,039438	0,000009	0,030685	0,026308	0,021931	0,017554	0,013178	0,008801	0,004424	0,000047
A13	0,040610	0,036556	0,000014	0,028448	0,024394	0,020340	0,016287	0,012233	0,008179	0,004125	0,000071
A14	0,052298	0,047082	0,000027	0,036650	0,031434	0,026218	0,021001	0,015785	0,010569	0,005353	0,000137
A15	0,040106	0,036108	0,000025	0,028112	0,024114	0,020116	0,016118	0,012121	0,008123	0,004125	0,000127
A16	0,052728	0,047488	0,000065	0,037007	0,031767	0,026527	0,021287	0,016047	0,010806	0,005566	0,000326
A17	0,032279	0,029054	0,000006	0,022604	0,019380	0,016155	0,012930	0,009705	0,006481	0,003256	0,000031
A18	0,071825	0,064717	0,000148	0,050499	0,043390	0,036281	0,029173	0,022064	0,014955	0,007846	0,000738
A19	0,049370	0,044462	0,000057	0,034644	0,029736	0,024827	0,019919	0,015010	0,010102	0,005193	0,000284
A20	0,060506	0,054493	0,000076	0,042468	0,036455	0,030442	0,024429	0,018416	0,012403	0,006390	0,000378

Table 13. Effect of λ on ranking patterns of alternatives in composite programming

λ	0	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	1
A1	13	13	9	13	13	13	13	13	13	12	9
A2	5	5	8	5	5	5	5	5	5	5	8
A3	6	6	6	6	6	7	7	7	7	7	6
A4	15	15	17	15	15	15	15	15	14	14	17
A5	3	3	4	3	3	3	3	3	3	3	4
A6	9	9	10	9	9	9	9	9	9	9	10
A7	12	12	12	12	12	12	12	12	12	13	12
A8	1	1	1	1	1	1	1	1	1	1	1
A9	10	10	13	10	10	10	10	10	10	11	13
A10	17	17	15	17	17	17	17	17	17	18	15
A11	20	20	20	20	20	20	20	20	20	20	20
A12	14	14	18	14	14	14	14	14	15	15	18
A13	16	16	16	16	16	16	16	16	16	17	16
A14	8	8	11	8	8	8	8	8	8	8	11
A15	18	18	14	18	18	18	18	18	18	16	14
A16	7	7	5	7	7	6	6	6	6	6	5
A17	19	19	19	19	19	19	19	19	19	19	19
A18	2	2	2	2	2	2	2	2	2	2	2
A19	11	11	7	11	11	11	11	11	11	10	7
A20	4	4	3	4	4	4	4	4	4	4	3