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An Overview of Multi-Criteria Decision Analysis and the Applications of AHP and TOPSIS Methods

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Abstract
The integration of multiple technical, economic, environmental, and social criteria establishes Multi-Criteria Decision Analysis (MCDA) as a dependable decision-making tool in the context of interdisciplinary research. This study employs a literature-based methodology to illustrate how MCDA, particularly utilizing the Analytical Hierarchy Process (AHP) and TOPSIS models, has been utilized to tackle intricate decision-making issues. It also highlights the noteworthy discoveries derived from real-world applications, drawing upon previous research and case studies. This study explores the methodologies employed in the commonly utilized AHP and TOPSIS approaches, highlighting their broad applicability across various industries from 2000 to 2023.

Additionally, a comprehensive examination of the applications of MCDA has been organized into five distinct sectors, namely supply chain, healthcare, business, resource management, and engineering & manufacturing.

Keywords- Multi-criteria decision analysis (MCDA), Analytical hierarchy process (AHP), TOPSIS, Supply chain, Healthcare, Business, Resource management, Engineering & manufacturing.

1. Introduction

A well-known area of operations research that concentrates on decision analysis is called MCDA. To assist decision-makers in selecting the alternative or options that are most aesthetically pleasing to them, MCDA incorporates a comparative examination of many criteria. High-complexity judgments that would be too difficult to analyze using conventional intuitive human thinking techniques can now be done so with the help of MCDA. It breaks difficult judgments down into simpler ones, which are then evaluated and weighted according to the subjective skills of the decision maker.

The use of MCDA to compile the gathered decision contexts into a cohesive whole that gives people the knowledge and assurance they need to carry out a solution is not an absolute analysis; it does not offer the solution to the problem. Decision-makers can better grasp and get insights into a situation by delving deeper using organized decision data. The ability of MCDA to scale from individual assessments to complex group decisions made by multinational organizations and governmental agencies is one of its key characteristics.

1.1 Early History of MCDA

The early contributions that noticeably laid the roots of MCDA, eventually leading to its evolution, are briefly mentioned in this paper. To comprehend the foundations of MCDA, one must look back in time. For a more comprehensive study of early history, see (Köksalan et al., 2011). Benjamin Franklin, the American politician, wrote the first recorded article about MCDA. His "Moral Algebra" concepts were closely linked to decision analysis. In a letter to a friend (MacCrimmon, 1973), he outlines how he evaluates numerous perspectives to determine whether or not to follow a decision. As a result, decisions are fundamentally linked to a variety of perspectives, similar to how various criteria are used in modern theory. The notion of how fair elections function had been added to by the Marquis de Condorcet. Condorcet's paradox was one of his most famous works. In 1785, he devised the Condorcet voting technique, which is presently used to conduct fair elections with several candidates. Jean-Charles de Borda proposed the usage of summed rankings in 1784. This approach works by assigning numerical scores to items based on their rank. The category of outranking methods in MCDM was directly motivated by this development in voting systems. Set theory's founder, Georg Cantor, should also be noted because the set theory is widely used in the mathematical operations of several MCDA approaches. Decision analysis is based on mathematical notions, and one of the first to create them was Francis Edgeworth. He coined the term "indifference curve" in the year 1881. He is credited with establishing the foundations of utility theory and the well-known Edgeworth box in the year 1881, which is used to distribute resources.

The aggregate of conflicting criteria was done using a mathematical approach. MCDA can be used to approach decision optimization. Vilfredo Pareto also established the concept of Pareto-optimality, which is a study of efficiency. In the year 1926, Frank P. Ramsey's work is credited with establishing decision analysis. He was the first to develop the utility model, which became the foundation for decision analysis. This study on utility theory would subsequently serve as a foundation for Multi-Attribute Utility Theory, one of the most used MCDA methodologies (MAUT). Without a doubt, John von Neumann should be recognized for his contributions to economics, as he co-authored "Theory of Games and Economic Behavior" with Oskar Morgenstern in 1944. The utility theory, a significant contribution to MCDA theories, was further expanded by the principles of the mini-max theorem addressed in the book. Peter Fishburn's seminal work, Decision and Value Theory, published in 1964, and Utility Theory for Decision Making, published in 1970, is also worth mentioning. Gerard Debreu was a key figure in the early development of utility theory, particularly value theory. His work was featured in the 1959 book 'Theory of Value,' which was founded on the concept of value theory and subsequently inspired the category of value measuring methods that are addressed here.

ELECTRE stands for Elimination Et Choix Traduisant la Realité and was founded by Bernard Roy (Elimination and Choice Expressing Reality). ELECTRE techniques are reported to have originated in France around 1960. Bernard Roy worked for SEMA, a business that invented the ELECTRE approach in response to challenges with many attributes or dependencies. Although the ELECTRE approach was originally designed to just provide the best option, it began to be utilized in the rank evaluation as well. George Dantzig worked on linear programming, which is credited with being the forerunner of multi-objective mathematical programming. George was hired to work on the USA's SCOOP program in 1947, where he worked on inventing efficient simplex algorithms to solve linear programming issues. The book Linear Programming by Saul Gass popularised it. After that, Harold W. Kuhn and Albert W. Tucker used linear programming in nonlinear situations. Tjalling C. Koopmans proposed an "efficient vector" method for solving resource allocation problems in programming, which was a continuation of Pareto's earlier work and led to the development of multiple objective mathematical programming.

Abraham Charnes, R.O. Ferguson, and William Cooper in the year 1955 set the groundwork for goal programming. Although the phrase wasn't coined in that piece, it did lay out the fundamental ideas and procedures. Zadeh, who invented the fuzzy set theory in the year 1965 (Zadeh, 1965), also contributed an innovative contribution. In contrast to the binary character of crisp sets, the elements of fuzzy sets have a degree of membership to a set. To deal with real-world problems that are often ambiguous and uncertain in classification, most MCDA methods have been adjusted to work with fuzzy sets. All of these publications had a substantial impact on the development of the MCDA theory and its applicability to real-world issues. As a result, the 1970s might be broadly regarded as the beginning of MCDA. Many popular publications on MCDA, such as (Roy, 1968; Keeny & Raiffa, 1993; Hwang & Yoon, 1981; Saaty, 1980), can be used to popularize the theories (Belton & Stewart, 2002). Figure. 1 represents the records reviewed for this study.

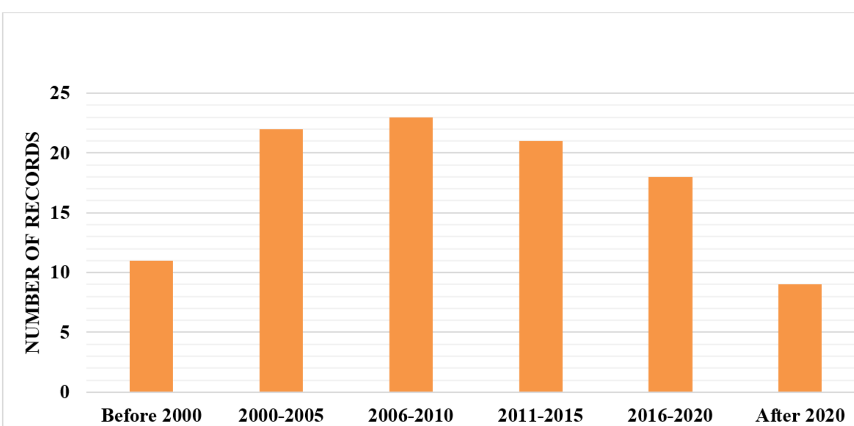

Figure 1. Records of significant work done in MCDA using AHP and TOPSIS.

1.2 The Need for MCDA

In this modern era of rapid progress, humans have been grappling with the need to make increasingly difficult decisions as technology advances. The advancement of modern technology, computation, and mathematical tools has benefited MCDA in realizing its enormous potential for problem solutions. MCDA's usefulness in management and development in today's world has been demonstrated in several previous research. The exponential increase of research activity on MCDA is highlighted in a study (Guerrero-Baena et al., 2014). According to this study, just 81 studies were published in the 1990s, but roughly 239 research papers were produced between 2001 and 2012. Computer Science, Engineering, Operational Research, and Business & Economies were the subject areas of this research with the most percentage of studies classified in them.

Traditional decision-making methods, such as the monetary technique, which includes cost Effective analysis, cost Benefit Analysis, and financial analysis, do not include all aspects of a situation (Donais et al., 2019). The MCDA approach to decision analysis is thought to be a new OR approach. It adds a degree of subjectivity to problem-solving by taking into account the decision maker's preferences. As a result, MCDA can be used with other classic OR approaches, filling in the gaps in both ways (Zavadskas et al., 2014), and so blending objective traditional methods with the subjectivity of MCDA methodologies.

1.3 Problems Approached by MCDA

Most real-world situations have many dependencies, and when it comes to analyzing a decision, a variety of elements come into play (Kumar & Pant, 2023). These challenges frequently have contradictory criteria, as well as multiple solutions (Kumar et al., 2022a, Rawat et al., 2022). A problem may have properties that differ in its measurement units, implying that they are of differing quality. Furthermore, some decisions may necessitate the collaboration of numerous decision makers, as is common in corporate strategy development. Because there is no such thing as an objectively optimum action plan in real life, many situations necessitate an awareness of the trade-offs among numerous features to arrive at the most subjectively ideal solution (Kumar et al., 2022b). Many situations are ambiguous, and there are no hard and fast rules for identifying some attributes, therefore decision-makers must weigh many uncertainties while making decisions.

To solve such challenges, MCDA tries to either design the best option or choose the best option from a set of a finite number of options. One major feature of MCDA is its scalability, which allows it to be used for a wide range of issues, from individual decisions to complicated group decisions made by multinational organizations and government agencies.

1.4 Alternatives

Alternatives could be explained as the multiple choices of action which can be implemented in response to a problem. They serve as a possible solution to reach the objective that the decision maker is trying to achieve. In the first step of MCDA which is problem structuring, alternatives are to be identified and properly organized. The selection of the most suitable alternative is done by ranking each alternative by providing a numerical score. An alternative numerical score is calculated based on the attributes it possesses. MCDA is capable of handling only a finite number of alternatives. Some basic features of alternatives to keep in mind while identifying alternatives are:

- It must be readily available.
- It must be easy to compare for evaluation.
- It must be realistic as well as tangible action.

- It must incorporate a few uncertainties to account for
- It must be feasible to implement in the real world.

1.5 Criteria
Criteria could be explained as a set of attributes, objectives, values, or characteristics of the problem sets which have a significant effect on the objective. They serve as a basis of evaluation for the alternatives by the stakeholders or actors. Criteria are the elements on which the objective is dependent. In the first step of MCDA which is problem structuring, criteria are to be identified and properly organized. A decision problem might contain several conflicting criteria and at times having multiple interdependent criteria in a problem might lead to false conclusions. Criteria of a certain real-world problem may incorporate multiple layers hence criteria could be divided into sub-criteria. Keeny & Raiffa (1993) suggests that five major principles be considered for the criteria-

- Completeness- All of the significantly relevant characteristics of the Decision maker's problems must be enfolded by criteria.
- Operational ability- The criteria must be functional. The criteria should be less elusive and straightforward to interpret. Also, criteria should have readily available research material and be meaningful for decision makers.
- Decomposability- The criteria could be divided down into multiple layers as sub-criteria. However, these sub-criteria must have a definite hierarchy.
- Non-redundancy- Two or more criteria measuring the same performance could result in false conclusions. Although many problems may have interdependent criteria, this should be avoided during the identification of criteria.
- Minimum size- Performing MCDA on real-world problems is time and resource-consuming. Hence, the decision maker must tend to reduce the total number of criteria to a sensibly adequate least number.

1.6 Decision Matrix
The decision problem has to be numerically represented for the application of mathematical procedures. This is done by forming a matrix called a decision or performance matrix in which alternatives are taken as rows and criteria are taken as a column. Each element of the matrix describes the performance of the alternative against each criterion. Hence a decision matrix serves as the basic structure to perform further mathematical procedures.

A decision matrix has an order of $m \times n$, where, m corresponds to the total number of alternatives, n corresponds to the total number of criteria. Hence, the element x_{ij} is the numerical score of the alternative A_i concerning criteria C_j, where, $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$.

$$\begin{array}{ccc} & & \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ X = & \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{1}$$

1.7 Scoring
The performance of each alternative based on the available criteria is allocated a numeric value or partial value function. An alternative with a better score in regards to particular criteria represent a better performance of that alternative. The score must belong to a well-defined interval scale to maintain relevancy against each other for instance a score could belong to a simple zero to a hundred interval.

1.8 Weighting

Eliciting weights to the criteria is simply constructing order of importance among the criteria to the actor depending upon the actor's judgment. The decision maker determines a numerical value based on relative importance. The elements of the weight vector should have the additive sum of 1.

1.9 School of Thoughts

There are multiple ways to categorize methods used in MCDA, a broad categorization is discussed below (Belton & Stewart, 2002):

a) Value Measurement Models

These types of models are based on the value theory of economics. The working principle of this method is that the decision elements are allotted a quantitative value to construct a level of preference amongst them. The assigning of value can be done by simply providing a numerical value as a score based on a simple scale or by constructing partial value functions (Belton & Stewart, 2002). The preferences are evaluated in such a way that if there are two options to be evaluated, one of them has to be more favored over the other one, or both are equally favored. Hence preferences have completeness properties.

An explanation for transitivity property which preferences inherit is also provided;

Let's consider the alternatives $x, y,$ and z, that is to be compared.
If $x > y$ and $y > z \Longrightarrow x > z$.

The most basic of all value measurement models is the additive model. The value function is calculated through addition. Hence, an alternative value is calculated through the formula –

$$V(a) = \sum_{i=1}^{m} w_i v_i(a) \tag{2}$$

where, *V(a)* represents the value of alternative a, $v_i(a)$ represents the score of alternative a corresponding to criteria *i* and w_i represents the weight of criteria *i* given by the decision maker.

b) Goal or Reference Level Model

The goal programming laid down the foundations of this category of MCDA methods. In this method, each criterion has allotted a satisfactory level of achievement which determines the performance of an alternative of the most significant criteria. This method is considered "goal programing" due to the use of satisficing or reference levels approach. The first step performed by the decision maker is to structure the criteria according to an order of preference. The key criteria are evaluated for each of the alternatives until a satisfactory level of performance is reached. Alternative with the best performance has been opted for while all the remaining alternatives are eliminated. This is a continuous process with the selection of the next suitable alternative using the remaining alternatives and eliminating them from the decision space and hence providing a ranking of alternatives.

The process isn't data intensive and aims to provide the options which are closest to achieving these desirable goals or aspirations.

c) Outranking Models

The outranking method involves pairwise ranking all alternatives relative to each other on each criterion. These pairwise-ranking results are then combined. The objective is to obtain evidence to assess the top-ranked alternative overall. The method differs from the earlier value theory methods in the sense that preferences established in outranking methods are based on solid evidence. This is the reason these methods are generally more data intensive.

The method to outrank one alternative to the other is very similar to the principle of dominance. For instance, outranking occurs when the preference has to be evaluated for alternatives x and y, and their respective value preference is defined by functions $z_i(x)$ and $z_i(y)$ where i represents a particular criterion, then if $z_i(x) > z_i(y)$ then x is preferred to y. Popular methods in this school of thought are ELECTRE and Vlse Kriterijumska Optimizacija Kompromisno Resenje' (VIKOR) method.

2. Procedure

The way to approach a problem in MCDA follows a basic procedure. The process is discussed below in brief points

2.1 Problem Identification and Structuring

The first step of applying MCDA is to figure out the decision context. The problem statement is studied thoroughly to identify elements of the problems. These elements to be identified and structured generally include key players, decision makers, stakeholders, values, uncertainties, and constraints.

2.2 Model Building

In this stage, a few major steps start with defining possible alternatives to the problem, while figuring out the criteria to evaluate these alternatives. This is followed by eliciting scores. Each criterion is then elicited weights. This process of prioritizing is intuitive and simple.

2.3 Action Plan

It is in the decision maker's judgment to select and modify the most suitable MCDA model to implement on a particular decision. The erected action plan is implemented in this step. The mathematical procedure of the model is applied and results are derived. This is usually followed by sensitivity analysis and robust analysis which provides a layer of confidence to the result.

Figure 2 depicts the main steps of the MCDA procedure.

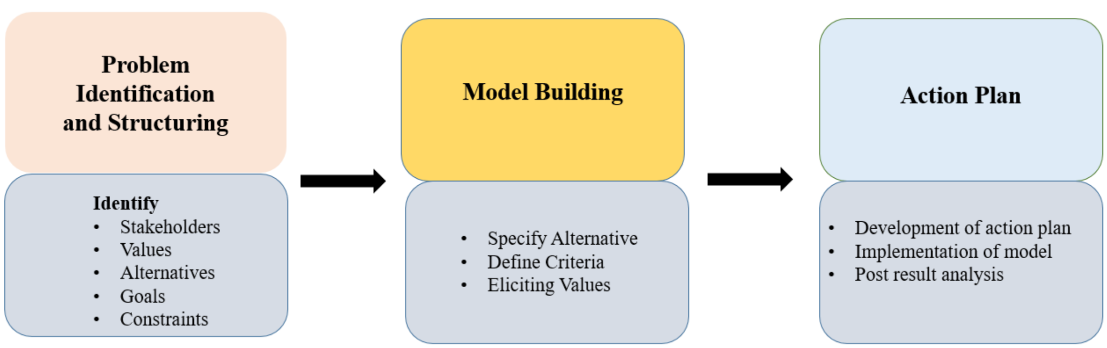

Figure 2. Flow chart of MCDA procedure.

2.4 Methodology

The basic methodology to approach any decision in MCDA is given below (Roszkowska, 2011). Let us put the multiple decision makers in a vector that can be denoted by,

$DM = \{1, 2, \dots, K\}$

Let 'm' be the total number of alternatives and the total number of criteria be 'n'. The decision matrix for the problem of order $m \times n$ would be denoted as in Equation (3)

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots\ldots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \ldots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \ldots & x_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^k & x_{m2}^k & \ldots & x_{mn}^k \end{bmatrix} \end{array} \quad (3)$$

or

$$X^{\mathrm{k}} = \left(x_{ij}^k\right) \quad (4)$$

where, $i = 1,2,\ldots,m$; $j = 1,2,\ldots,n$; $k = 1,2,\ldots,K$. Possible alternatives available to the objective are denoted by $A_i, A_2, \ldots, A_m$. The Criteria on which the objective is dependent are denoted by $C_1, C_2, \ldots, C_n$.

The element of the matrix x_{ij}^k denotes the performance of A_i corresponding to the Criteria C_j evaluated by the k decision makers. Now, let us denote the weight vector by $W^k = \left[w_1^k, w_2^k, \ldots, w_n^k\right]$. W^k is a weight vector for the k-decision maker, and

$$w_1^k + w_2^k + \cdots + w_n^k = 1 \quad (5)$$

Now, this was for the case of group decision making. When we are a single decision maker, we can simply represent the terms as $x_{ij}, w_j,$ and X.

3. Analytical Hierarchical Process (AHP) Model

The Analytic Hierarchy Process (AHP), has turned out to be a protuberant methodology in the territory of decision-making, particularly in situations involving multiple criteria and alternatives. AHP compromises a structured and complete approach to evaluating complex decision problems, infringement them down into a pyramid of criteria and sub-criteria. This method assimilates both qualitative and quantitative aspects, obliging subjective judgments together with objective data (Saaty, 1980).

AHP decomposes a complex MCDA problem into a linear hierarchy structure that connects the decision context's objectives, criteria, and alternatives. The problem's criteria could be qualitative or quantitative, which is a big plus for problems when the criteria don't always have a measuring unit. The AHP approach employs pair-wise comparisons, in which each element in the lowest layers is compared to the items directly above it. The outcome can be used to compare the performance of each choice, guiding the decision maker to the most appropriate option while also providing valuable information about the others. AHP gives the problem a hierarchical structure, which allows it to be scaled to handle complex group decision-making difficulties as well as basic individual-level issues. It also can be easily extended or modified. AHP is a straightforward and straightforward strategy that relies on the decision maker's intuitive ability to compare problem parts. As a result, it is one of the most often used MCDA methods (Vaidya & Kumar, 2006). AHP can also be classified as a compensating model, as it allows for tradeoffs between criteria, which can be beneficial in certain situations.

According to Saaty's research, the number of criteria should be limited to seven to avoid inconsistencies and similar criteria that contradict (Saaty & Ozdemir, 2003). Furthermore, AHP isn't data-intensive, therefore it's only useful for problems when specific problem data isn't needed or available. Further research regarding AHP's flaws can be found in the next article (Munier & Hontoria, 2021) Several extensions have lately been developed to further reduce inconsistencies by merging various computational strategies. (Aguarón et al., 2021).

3.1 The Hierarchical Structure

AHP provides a specific perspective to problem-solving by decomposing it into a hierarchy. This process breaks down the complex and usually messy problems into a fairly simple organized structure interconnecting the goal, criteria, and alternatives. This structure is linear. This structure serves as the guiding flowchart and provides focus to the decision makers.

Although the structure can be modified according to the needs of a decision maker, it would involve these 3 basic levels:

***Level* 1:** The topmost level defines the major objective or goal of the problem which the decision maker is seeking to do.

***Level* 2:** The intermediate level defines the criteria on which the performance of our solutions is to be evaluated. This level could be expanded to include sub-criteria by making a lower sub-level interconnected to the criteria which sit on the higher hierarchical order. This level could also include a sub-level of multiple decision makers in case of group decision-making. This sub-level would lie on top of the criteria sub-level.

***Level* 3:** The lowermost level defines the possible alternatives to the problem. This layer could also include sub-alternatives in particular decision problems. Figure 3 is depicting these levels.

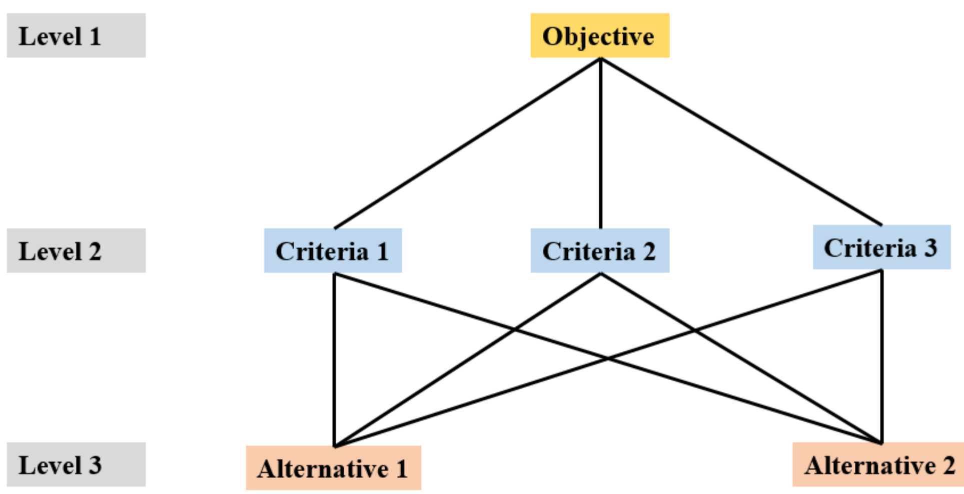

Figure 3. Hierarchical structure of AHP.

3.2 Procedure

The procedure to approach a problem using AHP can be generalized into 4 basic stages based on the works of Saaty (1980).

Identification of decision elements- The procedure begins with figuring out the decision context. The problem statement is studied to define the objective and identify various elements relevant to the objective of the problem.

Formation of hierarchy- All the elements of the problem are laid in a linear hierarchical structure by the decision makers in a manner explained in the above part. The objective serves as the first level, followed by the level of criteria, and then the lowest level is occupied by possible solutions or alternatives.

Formation of pairwise comparison matrices- The mathematical procedure begins with determining the preferences among all criteria which are achieved by decision makers through the construction of a set of pairwise comparison matrices. A scale called the Saaty scale is used for pair comparisons by providing a numerical value specified in a certain interval denoting how the preference or level of importance between two criteria. "Each element in an upper level is used to compare the elements in the level immediately below concerning it." (Saaty, 2008). Hence, alternatives are compared based on the criteria.

Deriving weights- Normalization has to be performed on the pairwise comparison matrices to the sum of one. The normalized scoring obtained from the comparisons is used to calculate weightage. There are various mathematical methods to calculate weightage. This is followed by consistency checks. The final scores of each alternative are calculated by taking the sum of the product of its score concerning each criterion and criteria weight.

3.3 Methodology

The methodology to approach a problem is provided below based on various research works (Saaty, 1980, 1990). The formula to determine the number of judgments, *J*, that have to be performed in a full pairwise comparison.

$$J = \frac{n(n-1)}{2} \tag{6}$$

where, *n* is the number of criteria.

To elicit scores, a comparison matrix is defined. The elements of the matrix represent the relative scores of criteria provided by the decision maker.

Let us define a pair-wise comparison matrix A of order $n \times n$ as

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix} \tag{7}$$

where, a_{ij} represents scores obtained by comparison.

The diagonal elements in the matrix A are compared against each other, hence $a_{ij} = 1$, where $i = j$ and $i, j = 1, 2, \dots, n$.

Also, the elements of the matrix are all positive and have the reciprocal property.

$$a_{ij} = \frac{1}{a_{ij}} \text{ for } a_{ij} \text{ and } a_{ij} = \frac{a_{ik}}{a_{jk}} \tag{8}$$

$$A = \begin{bmatrix} 1 & a & \dots & w_{1n} \\ a_{21} & 1 & \dots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \dots & 1 \end{bmatrix} \tag{9}$$

The eliciting of scoring elements against each other is done through Saaty's scale. A numerical value in between 1-9 can be allocated to each comparison. The Saaty's scale is described in Table 1 in detail.

Table 1. Saaty's scale.

Intensities of Importance	Definition	Meaning
1	Same	Equal importance to both the elements.
3	Weak	One element is just remotely of more importance.
5	Clear	One element is of clear importance.
7	Strong	One element possesses a strong degree of importance.
9	Very strong	One element possesses the strongest possible importance in comparison.
2, 4, 6, 8	Intermediate values	These are simply the intermediate values for more precision.
$\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}, \frac{1}{6}, \frac{1}{7}, \frac{1}{8}, \frac{1}{9}$	Reciprocals	Reciprocals of the above values.

The AHP most commonly uses two techniques to determine the final weights: the eigenvector method and the geometric mean method.

3.3.1 Eigenvector Method

The eigenvector method was first introduced by Hwang and Yoon in 1981 (Hwang & Yoon, 1981). The weight vector is represented by the principle of eigenvalues of the decision matrix while also being used as a parameter to prevent inconsistencies in the decision maker's judgment using the mathematical procedure for checking for inconsistencies in the decision matrix (Saaty & Vargas, 2001). Recalling Equation (8), the value of $\frac{w_i}{w_j}$ is often not determined in real-world problems. It is for that reason, a challenging task to find the value of a_{ij} such that $a_{ij} \cong \frac{w_i}{w_j}$.

This gives us our reciprocal weight matrix as:

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \frac{w_1}{w_2} & \vdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \vdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \vdots & 1 \end{bmatrix} \tag{10}$$

Every matrix developed as a set of eigenvalues and eigenvalues makes up eigenvectors. The weight vector is the normalized eigenvector having the largest eigenvalue, then the following formula shows how weights are calculated.

Firstly let, the eigenvector of weights be denoted by $w = [w_1, w_2, \dots w_n]^T$.

On multiplying matrix A with the weight vector w we get,

$$A.w = \begin{bmatrix} 1 & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \dots & \frac{w_2}{w_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & 1 \end{bmatrix} . \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \approx nw \quad (11)$$

or

$$(A - nI).w = 0 \quad (12)$$

The equation is the eigenvalue problem which can be solved by linear algebra.

Solving the equation for λ_{max} gives us the elements of the weight eigenvector w. Hence, it must be solved in a way that satisfies the equation.

$$(A - \lambda_{max} I).w = 0 \quad (13)$$

where, λ_{max} denotes the largest eigenvalue for the matrix, and

$$\lambda_{max} \geq n \quad (14)$$

3.3.2 Geometric Mean Method

The method of taking the geometric mean of a row was first presented by Saaty (2001). Firstly, the product of 'n' number of elements is done in each row. The nth root is taken for each row.

The resulting values are made into a new normalized column. This normalized vector is the weight vector. The formula used in this method is

$$r_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \rightarrow w_i = \frac{r_i}{\sum_{i=1}^{n} r_i} \quad (15)$$

where, n is the number of alternatives and r_i is the weight vector; $i = 1, 2, \dots, n$.

3.4 Consistency Check

With a large number of alternatives, it becomes increasingly difficult to prevent inconsistencies. However, each problem can be processed under a consistency check. Inconsistencies can happen for multiple reasons: lack of judgment of the decision makers, lack of information available, real-world problems being vague, or there could be problems within the model building as well.

To monitor for consistency, a consistency Index which is used to check for inconsistency in the decision matrix is calculated by the formula,

$$CI = \frac{(Principal\ Eigenvalue - size\ of\ matrix)}{size\ of\ matrix - 1}.$$

or

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (16)$$

Next, the consistency index is compared to the Random Index (RI), where RI is a randomly generated positive reciprocal matrix. One property of it is that it can have any possible order, though the RI of the same order as our matrix has to be taken for further calculation. The RI values of matrices up to an order of 10 are in Table 2.

Table 2. Random index value.

Order	RI
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

Then Consistency Ratio (CR) is calculated. The ratio between the consistency index and the random index gives the CR, which is unaffected by the size of the matrix.

$$CR = \frac{CI}{RI} \tag{17}$$

Generally, when $CR < 0.1$ then the comparison matrix is taken to be consistent and hence a reliable conclusion can be drawn from it. When $CR > 0.1$ then the comparison matrix incorporates many inconsistencies and might result in a false conclusion.

Ideally, the matrix is considered fully consistent when

$$\lambda_{max} = n \tag{18}$$

Hence, in that case, $CR = 0$.

With this, the only step remains to determine the final global rankings of the alternative. The final scores of each alternative are calculated by taking the sum of the product of its score for each criterion and criteria weight.

3.5 Sensitivity Analysis

Most MCDA approaches are used on real-world problems that are ambiguous to measure numerically or can be altered because of their sensitivity to uncertainties. Thus, the decision maker needs to know how changes in the initial setting problem can reflect in the results for making a more confident decision.

Sensitivity analysis of AHP is specifically useful because of the following nature of AHP (Erkut & Tarimcilar, 1991).

The Decision Maker's subjective judgment of plays a significant role in the evaluation of important criteria. Such use of subjective decision-making surges the chances of uncertainty, which calls for sensitivity analysis.

As discussed earlier, the AHP method may include inconsistencies in the comparison matrices. Also, AHP isn’t data extensive and doesn’t require precise input data. This nature of vagueness of AHP and the real world can be kept in check with sensitivity analysis.

3.6 Rank Reversal
Rank reversal is a phenomenon that can be possibly noticed when a change in the number of alternatives is introduced in the decision problem. What rank reversal is that usually when a new alternative is considered, it is noticed there is a change in the global rank of other alternatives.

AHP is prone to the problems of rank reversal as it doesn't take into account the possible correlation between alternatives. One way to explain rank reversal is based on the weighted sum aggregation method. This can be done by either adding the weights of criteria and then performing normalization to obtain the weight vector and hence final rankings of alternatives or as done in AHP, normalization is performed on the decision matrix of scores, and then the weighted sum value of criteria is taken to obtain weight vector. This method used in AHP causes rank reversal as it ignores the fact that the unit of scale used for the normalization of weights between specified intervals may differ for different criteria (Zahir, 2016).

In conclusion, this study highlights the importance of MCDA as a strong decision-making tool in the dominion of interdisciplinary research. By assimilating various procedural, economic, environmental, and social criteria, MCDA appears as a dependable method for handling complex decision-making challenges. The literature-based methodology engaged in this study provides comprehensions into the effective use of MCDA, mostly through AHP and TOPSIS models.

The investigation of AHP and TOPSIS methods reveals their extensive application across various industries from 2000 to 2023, highlighting their adaptableness and effectiveness. Real-world uses, depiction from former research and case studies, contribute to the empathetic of the real-world insinuations and success stories allied with MCDA methodologies.

Furthermore, the delineation of MCDA submissions into specific sectors- supply chain, healthcare, business, resource management, and engineering & manufacturing- provides a structured overview of the versatility of MCDA in addressing distinct decision contexts. This study not only contributes to the theoretical understanding of MCDA but also highlights its practical implications, offering valuable insights for researchers, practitioners, and decision-makers across various domains. The integration of MCDA methodologies, particularly AHP and TOPSIS, stands as a testament to its enduring relevance and applicability in navigating the complexities of decision-making in diverse fields over the past two decades.

4. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Model
The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) has emerged as a commanding methodology in the field of MADM. Originally proposed by Hwang and Yoon in 1981, TOPSIS has grown eminence for its capability to systematically assess and rank alternatives (Hwang & Yoon, 1981).

In the site of decision-making, mainly when confronted with complex decision problems involving miscellaneous and often conflicting criteria, TOPSIS delivers a structured approach. This method comprises the assessment of alternatives built on their propinquity to the ideal solution and farthermost from the negative ideal solution in an MCDM.

In 1981, Hwang and Yoon introduced a new method called Technique for order preference by similarity to ideal solution (TOPSIS) as an alternative to the ELECTRE (Hwang & Yoon, 1981). When compared to other alternatives in the decision space that may have multiple dimensions, the most suitable solution must be geometrically positioned to have the shortest distance from a theoretical concept of the best solution' while simultaneously being at the longest distance from the opposite value of the best solution, i.e. worst solution. The Euclidean distance is commonly used to assess the relative closeness of alternatives to the ideal solution because it is sufficient and requires minimal computational resources.

Because of arguments that the suitable alternative should be farthest from the worst solution at the same time, the geometrical distance from the worst solution is used to determine the closest alternative to the best answer. Because it is functioning in a decision space with more than one dimension, the alternative with the shortest geometrical distance from the best answer was sometimes positioned in such a way that it had a significantly shorter distance to the worst solution than some other alternative(s). (Hwang & Yoon, 1981).

Figure 4 is depicting the decision context in the two-dimensional decision, to provide a better geometrical perspective.

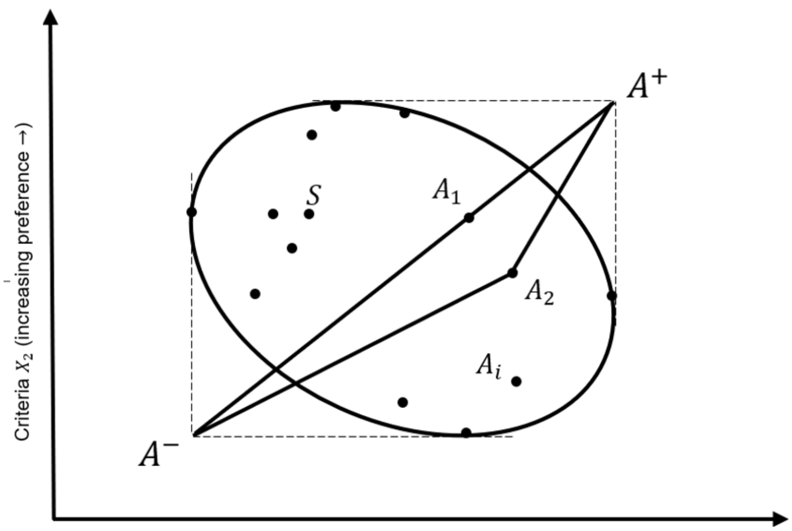

Figure 4. Representation of decision space.

The TOPSIS technique, on the other hand, is constrained since it presupposes that the usefulness of each criterion increases or decreases monotonically (Hwang & Yoon, 1981). The value of relevance to the decision maker is known as utility. This makes calculating the value of the best solution quantitatively simple and understandable. The relative distances of all options to the greatest solution can be used to determine the final rankings of each alternative. TOPSIS has grown in popularity as a result of its simple-to-use approach. The mathematical approaches used are straightforward. Because TOPSIS is easily programmable, its use has risen in tandem with the advent of computing. One of the most notable features of TOPSIS is that the number of steps in the technique does not increase as the number of criteria increases. According to a study, TOPSIS had the least rank reversal among AHP and ELECTRE (Zanakis et al., 1998).

TOPSIS, on the other hand, has a few flaws, one of which is that it ignores the correlation of criteria when calculating the relative distance of alternatives to the ideal answer using Euclidean Distance. The method has been criticized for failing to integrate consistency of the decision maker's judgments (Velasquez & Hester, 2013).

4.1 Ideal Solution
A theoretical solution to the problem statement's purpose that acts as the perfect or best solution to the objective is known as an ideal solution (also known as an optimum solution). Criteria can be divided based on whether the alternate performance of that criteria is effectively beneficial or unfavorable.

The profit criterion category, often known as benefit criteria, includes criteria where improving the performance of an alternative for that criteria will also enhance the benefits. The unfavorable criteria category, often known as the cost criteria category, includes factors for which improving the performance of an alternative will reduce the advantages.

As a result, the value of all profit criteria would be the highest for optimal solution performance, while the value of all cost criteria would be the lowest. This generates a utopian situation in which the decision's goal is achieved perfectly.

The TOPSIS methodology is founded on the compromise methods school of thought. Because the ideal answer is theoretical and unlikely to exist in the real world, compromising approaches address this by accepting a compromise to select the most effective alternative. TOPSIS selects the geometrically closest alternative to the optimal solution based on the theory.

4.2 Methodology
The methodology to perform the TOPSIS model will be discussed now. It has been divided into a series of steps.

***Step* 1.** The procedure begins with the construction of the decision matrix with a total number of alternatives denoted by m and the total number of criteria denoted by n. The order of the decision matrix will be $m \times n$.

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{19}$$

where, the alternatives are denoted by $A_1, A_2, \dots, A_m$ and the criteria are denoted by $C_1,\ C_2\ , \dots, C_n$. x_{ij} is the element of the matrix which denotes the decision maker assessment of alternative A_i for $i = 1,2, \dots, m$ concerning the Criteria C_j for $j\ = 1,2, \dots\ , n$, and $x_{ij} \in \mathbb{R}$.

The criteria weights are to be determined by the decision maker in a vector. Let the weight vector be $w = w_1, w_2, \dots, w_n$, where, $w_j \in \mathbb{R}$, and the total sum of weights is one, hence $\sum_{j=1}^{n} w_j = 1$.

***Step* 2.** The criteria are for different quantities having different units of measurement. To perform evaluations on such criteria it is necessary to normalize them. Normalization is performed on the decision matrix to bring the elements into a specified range. The formula to normalize the decision matrix is given as

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2} \tag{20}$$

where, R is the normalized matrix with the elements r_{ij} for $i = 1, \dots, m;\ j = 1, \dots, n$.

There are several other formulae for normalization.

***Step* 3.** The weighted normalized decision matrix is formed by calculating the product of the normalized decision matrix and the weight vector is done which gives the weighted normalized value v_{ij} as

$$v_{ij} = w_j . n_{ij} \quad \text{for } i = 1, \dots ,m;\ j = 1, \dots ,n \tag{21}$$

Let the weighted normalized matrix be represented as,

$$V = (v_{ij}) \tag{22}$$

$$V = \begin{bmatrix} w_1 n_{11} & w_2 n_{12} & \dots & w_n n_{1n} \\ w_1 n_{21} & w_2 n_{22} & \dots & w_n n_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 n_{m1} & w_2 n_{m2} & \dots & w_n n_{mn} \end{bmatrix} \tag{23}$$

***Step* 4.** The best solution is referred to as a positive ideal solution (PIS) and the worst solution is referred to as a negative ideal solution (NIS). Now let us denote a PIS by A^+ and NIS by A^-, then

$$A^+ = (v_1^+, v_2^+, \dots, v_n^+) = \left\{\left(\max_{\mathrm{i}} v_{ij} | j \in I\right), \left(\min_{\mathrm{i}} v_{ij} \mid j \in J\right)\right\} \tag{24}$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-) = \left\{\left(\min_{\mathrm{i}} v_{ij} | j \in I\right), \left(\max_{\mathrm{i}} v_{ij} \mid j \in J\right)\right\} \tag{25}$$

where, I is associated with benefit criteria, J is associated with cost criteria for $i = 1, \dots, m$; and $j = 1, \dots, n$.

***Step* 5.** The geometric distance between the PIS and the NIS of each alternative is determined as geometric distance. Geometric distance from the PIS and NIS is calculated by (26), and (27) respectively.

$$d_i^+ = \left(\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^p\right)^{\frac{1}{p}} \tag{26}$$

$$d_i^- = \left(\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^p\right)^{\frac{1}{p}} \tag{27}$$

where, $i = 1,2, \dots, m$ and $p > 0$.

The Manhattan distance, The Euclidean distance, and Tchebycheff distance is used for $p = 1$, $p = 2$, and $p = n$ respectively. Most usual problems are dealt with in 2-dimensional decision space, therefore Euclidean metric is used. Hence, these equations become

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \text{ for } i = 1,2, \dots, m. \tag{28}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \text{ for } i = 1,2, \dots, m. \tag{29}$$

***Step* 6.** The relative closeness to the positive ideal solution is determined with the help of closeness coefficient. The relative closeness of the ith alternative, A_i for A^+ is given as

$$R_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{30}$$

where, $0 \leq R_i \leq 1,\ i = 1,2,\dots,m$ and R_i is the closeness coefficient.

***Step* 7.** The final step is to give global rankings to alternatives. The ranking is done based on the value of the closeness coefficient R_i in a manner that follows a decreasing order that is higher the value of its closeness coefficient of an alternative, the lower its rank is.

Hence alternative with the R_i closed to 1 is regarded as the most suitable alternative for the decision problem. Figure 5 represents the flowchart that summarizes the TOPSIS procedure.

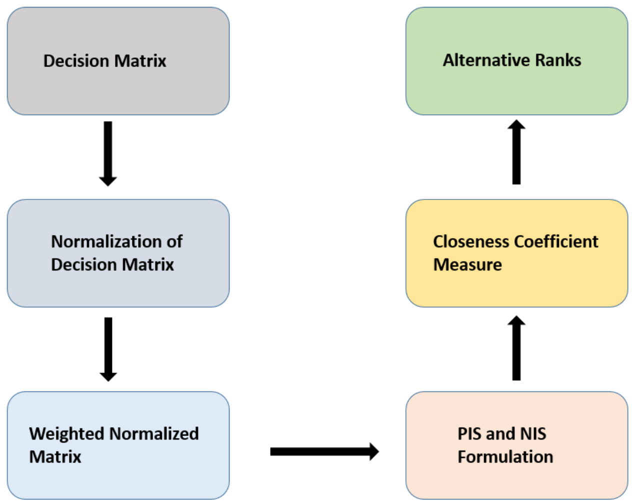

Figure 5. Flowchart of TOPSIS procedure.

5. Applications of MCDA

Multiple contributions have been made in the field of MCDA; there are layers to it - research based on real-world situations, case studies, and certain literature reviews that summarise MCDA applications. The research is a little disjointed. Recently, there has been a considerable gap in work done in reviews of the use of AHP and TOPSIS across many application domains compared to the multiple research on problem-solving, based on purely quantitative data discovered during this study. A review can help to encourage further evolution by identifying potential flaws in the existing literature and promoting additional evolution based on the foundation laid by others.

Some previous work demonstrates the bibliometric of how much MCDA is applicable in everyday life, although AHP remains the most often used method (Pant et al. 2023, Sharma et al. 2023). AHP is primarily used to solve resource allocation, performance, and policy issues (Vaidya & Kumar, 2006). Another prominent method for application ranking, evaluation, and selection problems is TOPSIS.

This section attempts to describe the applications of AHP and TOPSIS, respectively. Its goal is to condense a large body of research into a concise but comprehensive review of MCDA, as well as to add to the current knowledge base. Keeping this in mind, this research divides the app into broad categories to cover a wide range of applications. This study goes through the recent two decades' studies to explain how MCDA has been utilized in the past and is being utilized in the present modern era.

Hence, the applications are divided into 5 broad categories: supply chain, health care, business, resource management, and engineering and manufacturing.

The research articles reviewed were chosen from three databases for this investigation. SCOPUS, Web of Science, and the Institute of Electrical and Electronics Engineers Xplore (IEEE) are some of the publishers that are easily accessible over the internet. Additionally, many publications were reviewed during the development of this study to offer eclectic research; this divergence was required to provide a thorough perspective of how AHP and TOPSIS affect our lives.

The period covered was 2000-2023, demonstrating how far MCDA has progressed in recent years. In total, a brief review of articles based on AHP and TOPSIS applications has been provided next. Figure 6 and Figure 7 represent a summary of these research studies. Table 3 represents a comparative view and need of this study.

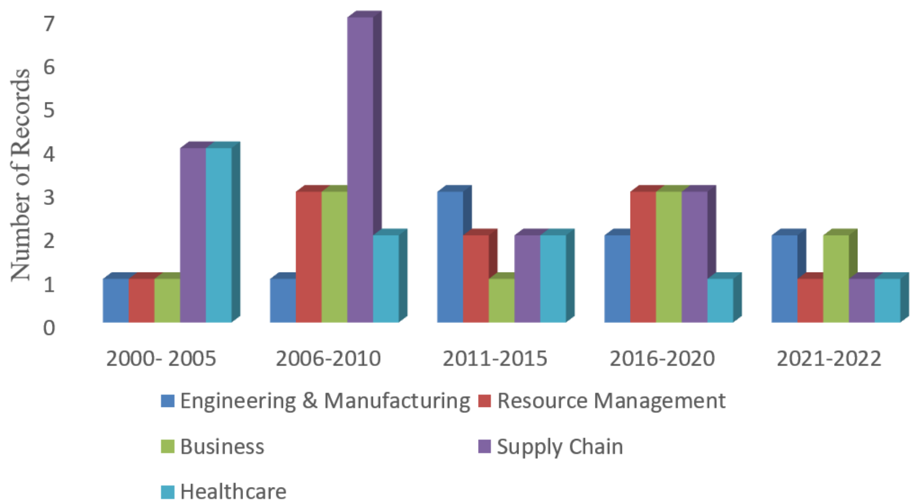

Figure 6. Records of significant work done in MCDA using AHP.

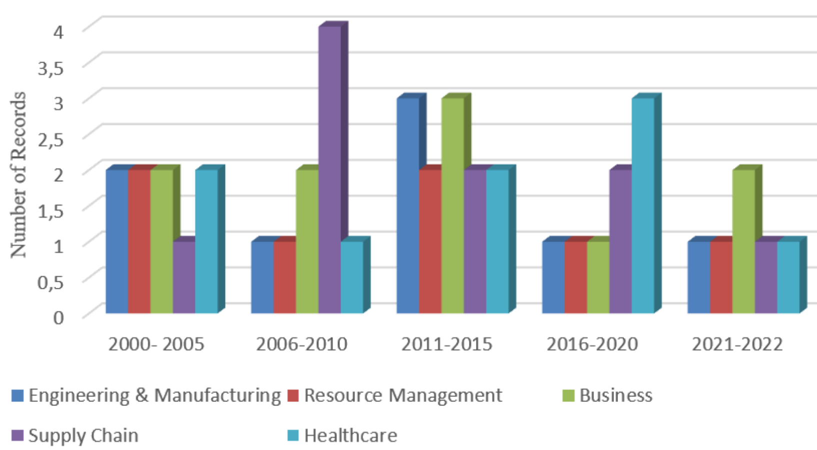

Figure 7. Records of significant work done in MCDA using TOPSIS.

Table 3. Comparison with existing studies.

Study	Method	Area
Franek & Kashi (2014)	AHP, TOPSIS	Business
Ilbahar et al. (2019)	AHP, TOPSIS	Engineering
Yannis et al. (2020)	AHP, TOPSIS	Transportation
Tariq et al. (2020)	AHP, TOPSIS	Healthcare
Gyani et al. (2022)	AHP, TOPSIS	Engineering
Zayat et al. (2023)	AHP, TOPSIS	Engineering
Pandey & Dincer (2023)	AHP, TOPSIS, WASPAS	Engineering
This Study	AHP, TOPSIS	Supply chain, healthcare, business, resource management, engineering & manufacturing.

5.1 Supply Chain

MCDA is incredibly useful in many aspects of the supply chain. Most areas of applications are a selection of suppliers, supply chain management, quality or performance assessment, risk assessment, distribution network management, and site allocation of warehouses.

Masella & Rangone (2000) created a basic AHP model for choosing the best vendor. To achieve so, the relationship between a buyer and a supplier was defined based on the time interval and nature of integration, and an AHP-based vendor selection approach was proposed for each type of relationship. AHP has also been proven to help with performance issues. Lee et al. (2000) employed a simple AHP model to improve supply chain performance in a Korean air conditioning company using main and minor criteria for precise improvement in the same year. Humans are becoming increasingly concerned about the environmental effects of their behavior. Handfield et al. (2002) were interested in considering environmental factors while making decisions, therefore they built an AHP model based on the notions of spending budgets while being environmentally sensitive. Pochampally & Gupta (2004) advocated utilizing a monetary method of cost-benefit functions based on fuzzy sets and goal programming to create a reverse supply chain. The study's final section employs fuzzy TOPSIS to determine the optimum reverse supply chain marketing approach.

Real-life situations are hazy and lack clear boundaries, making it impossible to assess the existence of features in a straightforward binary manner, such as yes or no. As a result, fuzzy sets, which assign entries a grade of membership to a set, are frequently employed to express such situations sensibly. The AHP approach only works with crisp sets and ignores uncertainty. Because AHP is so adaptable, it can be tweaked to work with fuzzy sets. The Fuzzy AHP model is used in a study by Feng et al. (2005) to handle the challenge of identifying items to be outsourced and selecting suitable vendors for them at the same time. Pang & Bai (2013) expands on the Fuzzy AHP model to handle the challenge of picking the most acceptable supplier based on a supplier's financial situation, management abilities, technical abilities, and quality in a comparable study. With technological improvements, information exchange has become a critical strategy for businesses. Zhang & Wang (2007) integrated AHP and TOPSIS to create a model for identifying knowledge-sharing partners among logistics-related businesses. AHP provides a hierarchy of decision context and uses the eigenvector method to derive weight vector, TOPSIS builds up on this to optimize the results. Hence a combination of both methods provided a reliable evaluation of the problem. Buyukozkan et al. (2008) aimed to provide a decision aiding system for a suitable e-logistics partner using Fuzzy AHP to provide structure and determine criteria weightage, further fuzzy TOPSIS is applied to evaluate the best performing partner for a strategic alliance.

Risk management is another crucial area where organizations can rely on MCDA methods. Kull & Talluri (2008) worked on risk management in a supply chain of an automotive supplier, a risk assessment was done followed by an integrated approach of AHP and goal programming to determine the most suitable supplier taking the possible risks into account. In the same year, a study by Fasanghari et al. (2008) worked on a study showing how Information Technology could improve aspects of supply change management with the eventual aim to improve supply chain agility in general. TOPSIS was utilized to inspect the improvement in agility by such aspects. The inclusion of sustainable development in the supply chain has become a major focus of the modern era. Zhang & Zhao (2009) used fuzzy AHP based on triangular and trapezoidal fuzzy numbers for performance evaluation of green chain supply in which supply chain is checked for sustainability depending upon certain green indicators. Another study by Yan (2009) in the same year approaches the similar concept of green chain supply with AHP combined with genetic algorithms for better optimization.

Analytical Network Process (ANP) is a modified variant of AHP which instead of a linear hierarchy structures the problem into a network that can be non-linear (Saaty & Vargas, 2006). The need for ANP was to handle correlation between decision elements which is ignored by AHP. It can also use a group of elements for prioritization instead of single elements. Lin & Tsai (2010) combined the use of ANP with TOPSIS to figure out the best location for a new hospital to maximize the benefit of foreign direct investment. The key criteria identified were government-related elements such as policies, demands, agglomeration effects, and factor conditions. TOPSIS has also been used frequently for deciding site locations. For instance, a study conducted by Alimoradi et al. (2011) aimed to combine forward and reverse supply chain concepts for the creation of a closed loop supply chain. For the recovery measure of the location of remanufacturing sites, Fuzzy TOPSIS was utilized to detect suitable site locations.

Rezaei & Ortt (2013) developed a methodology based on fuzzy AHP for the supply chain management. The methodology was applied to determine the supplier’s willingness and potential separately based on the buyer’s opinion and judgment. Fuzzy AHP was applied to calculate scores of each supplier on the willingness and potential and then the suppliers would be segmented and ranked based on these two factors with the help of a simple plotting graph with these two factors serving as an axis which also represents the trade-offs between the selection of supplier. Junior et al. (2014) conducted a study to compare fuzzy TOPSIS with fuzzy AHP for supplier selection and concluded that although both methods were adequate for this type of problem-solving, fuzzy TOPSIS notably had some advantages as fuzzy AHP is limited by the number of criteria and possible rank reversals.

Warehouse location selection for minimum costs and easy operations has been using MCDA for a long time. For instance, Singh et al. (2018) worked to provide the Indian government with an optimum location of warehouses in Iran based on establishment, government policies and laws, and business environment by using Fuzzy AHP for model building. MCDA is also useful in optimizing the distribution of networks in the supply chain, for instance, a study conducted by Akgün & Erdal (2019) used a model consisting of AHP and TOPSIS for the development a distribution network for military purposes is ammunition distribution units. The two major criteria were the cost of logistics of the multiple units allocated in the location would bring and the risk assessment done by the MCDA methods. Cherier et al. (2020) proposed the use of integrated AHP and TOPSIS methods to find the best quality of raw supply from tomatoes on farms in Algeria. AHP is applied to derive the relative priorities of decision makers and TOPSIS is applied to evaluate multiple tomato-produced farms available in the supply chain. Magableh & Mistarihi (2022) measured the negative impact of Covid-19 on supply chains globally. After identifying the impacts, the study also provides solutions and proposes the use of insights gained from comparing their relative effectiveness to figure out when and what solution to implement. This comparison is done through an integrated ANP-TOPSIS methodology.

5.2 Health Care

MCDA is often used in health care for personal purposes such as Patient Decision Aid methods, detection and evaluation of treatment, and risk assessments while on a more institutional purpose it comes into utilization in quality assessments, management purposes, solid waste management, public health evaluations and so on with the aim for providing assistance and better communication between health care workers patients

Dolan (2000) utilized AHP to develop a model that incorporates patient judgment for making decisions on preventive health interventions. This provided better communication between patients and health workers and improved the quality of clinical decision-making. Waste management of the hospital is a concerning issue that MCDA can answer to. In a study by Cheng et al. (2002), multiple MCDA methods have been applied simultaneously including the TOPSIS method to select the most beneficial landfill location in terms of practicality, recycling concerns, and cost for promoting solid waste management in Canada. Another study by Karagiannidis et al. (2010) based on Greece hospital waste management used AHP to recognize the most effective plant for treatment of waste using thermal processing.

Cho and Kim (2003) combined AHP with multi-attribute utility theory and elimination (MAUT) and choice expressing reality for analyzing and selecting appropriate medical devices when resources management has to be kept in check. Cheng (2005) conducted in Nanjing used AHP and TOPSIS combined to rank 10 public and non-profit hospitals depending on their quality of health care. The criteria the study used were the quality of the hospital's diagnostic, efficiency, treatment, and environment. Similar work but with a different methodology by Habibi et al. (2019) uses a combination of TOPSIS and Multi-Objective Optimization based on Ratio Analysis (MOORA) to rank hospitals based on their health care quality and services, this ranking could be useful information utilized in the betterment of public health services.

Cheng (2005) used to minimize the risk factors for falling which is a common cause of injury in the community of elder people. The risk elements are assessed with the AHP model with the help of experts' work experience and judgments. Dey & Hariharan (2008) used strengths, weaknesses, opportunities, and threats (SWOT) analysis to identify projects for the improvement of quality healthcare services in Queen Elizabeth Hospital, AHP method was then applied to evaluate the effectiveness of these projects. Chou et al. (2012) used the TOPSIS method to evaluate and select the best medical provider which is a concerning matter in tourism. The model was demonstrated in New York's medical providers based on the medical provider quality, services, tourism activities, transport, and food. Chen et al. (2014) aided patients in the selection of hospitals by the use of an AHP model and geographical data. Post-result analysis showed the majority of patients were satisfied with the usage of the model. AHP and TOPSIS methodology was used in a study by Zaidan et al. (2015) to decide on the selection of which open-source electronic medical record software is suitable for medical practitioners. The extensively used eight criteria were primarily based on concerns of ease of use, features, technology, security, support, and user preferences to decide amongst the multiple EMRs available online. Barrios et al. (2016) integrated AHP's criteria weighting procedure with TOPSIS evaluation of alternatives to analyze and select the most suitable tomography device hence providing a great deal of assistance to the medical workers and their patients as well.

MCDA can be used in studies researching the recent Covid-19 outbreak. Rahma et al. (2020) aimed to devise a diet plan and healthy lifestyle to fill up the needs of nutrients deprived bodies of Covid-19 recovered patients. The optimal diet plan and lifestyle depending on the person's age, weight, and intake was evaluated using the TOPSIS method. Shrestha et al. (2020) used the TOPSIS method to derive a Pandemic Vulnerability Index (PVI) for each country. This PVI was a measure for each country's health care capacity to fight against the outbreak of COVID-19. This study was utilized in measuring the impact of COVID-19 on global public health.

Basu et al. (2020) proposed the use of Convolutional Neural Networks (CNN) to detect breast cancer and provide adequate treatment consultation from doctors using the TOPSIS method in which the information provided by the detection procedure served as criteria.

5.3 Business

Most MCDA methods are useful in Business majorly for better financial decisions as well as managerial purposes. This can be done in several ways like management, strategy evaluation, optimization of processes, risk assessments, policy making, investment strategies, and so on.

Deng et al. (2000) used a modified variant of TOPSIS in which they used objective weights. The purpose of the study was to rank textile companies based on multiple parameters of financial ratios which is a comparison of two financial measurements of a company's statistics. Entropy measures were applied to determine the objective weights of the financial ratios. Zhou and Chen (2003) used TOPSIS to evaluate the quality of business processes. The business process is based on supply chain, resource management, and other factors. The study guides to improve the quality of the business process by taking past evident data and using TOPSIS to select resource allocation techniques geometrically close to the evident past allocations as the optimum solution. Lee & Kozar (2006) found that the quality of the business' online website directly influences the business's financials. The study used AHP on many criteria concerning e-commerce business like the technology, interface, convenience, and content to conclude that a better website is impactful on business growth.

Işıklar & Büyüközkan (2007) use AHP combined with TOPSIS to evaluate suitable mobile phone options for a buyer on a personal level. The study identified the two criteria based on multiple sub-criteria concerning the requirements of a typical buyer such as functionality, design, brand, technology, budget, and more. Similarly, another study by Ertugrul & Oztas (2014) used Fuzzy TOPSIS to evaluate mobile operators available on a large-scale institutional level. Communication is a necessity in huge business enterprises hence the study evaluates the best mobile operative for large companies to improve communication quality. Wu et al. (2010) developed an integrated model consisting of ANP and TOPSIS to devise an optimal marketing strategy and applied it in private hotel management resulting in a better understanding of their managerial capabilities and resource management.

Comparison of the business competitors is an important analysis that businesses need for the growth of their market share. Torlak et al. (2011) used TOPSIS working on fuzzy set theory to analyse the competition in the setting of Turkish domestic airline businesses. Rouhani et al. (2012) evaluated multiple enterprise systems in regards to business intelligence which was otherwise solely used to evaluate enterprise systems before purchasing, to work a large number of criteria involved the study proposed the use of Fuzzy TOPSIS for evaluation. Guerra & Jenssen (2014) provided a guide to stakeholders for investment in a new ship vessel in Norway using AHP while using system engineering for the formulation of the decision problem. The study took into account environmental parameters to tackle the strict laws and provide the stakeholders with a great value investment.

Businesses have been deeply analysing themselves for their growth in market share, Riahi & Moharrampour (2016) to provide for such requirements of business proposed an AHP-based model to select the best business strategy for resource allocation and handling. A case study was done based on this model for a household application-related company and the model suggested following a cost leadership strategy i.e. reduction in prices compared to competitors. Yap et al. (2017) used AHP to find the best site location for payment stores business in Malaysia. The criteria used in this were population metrics, location of site, conveniences, and how the site is positioned while the first has the highest priority. Ouenniche et al. (2018) developed a model to use TOPSIS as a classifier to evaluate firms in the UK on bankruptcy, by using the closeness coefficient measure of each firm against an ideal solution of a financially stable firm, the model was found to be too precise in the prediction of bankruptcy of firms. Büyüközkan et al. (2019) designed a model to use the most appropriate business intelligence system for the analysis of huge information into useful parameters for optimization of business processes using modified AHP for the development of such model.

Bae et al. (2021) compared the AHP method with TOPSIS and an integrated AHP-TOPSIS method all working on fuzzy set theory in a case study of evaluation of the airline industry's performance based on the working and econometrics. The integrated Fuzzy AHP-TOPSIS was found to be more insightful than the other two methods. Another study in the same year by Liang et al. (2021) in China aimed to develop rankings of cities in China based on the business environment. The entropy method of weighting was used to derive priorities and TOPSIS was further applied to evaluate the rankings of the cities, this provided benefits, and shortcomings in the business environment of each city.

Bathrinath et al. (2022) used the AHP model to assess the risk in the sustainability of the sugar production industry of the Indian region. AHP is often found useful for risk assessment as the criteria weights are determined by a reliable method of comparison. The study concluded with overconsumption of water as the most concerning risk element in the industry while also mentioning some other non-environmentally friendly practices and lack of proper information.

5.4 Resource Management

Resources are often limited to humans or are challenging to harness even if there is a non-exhaustive resource supply available, hence resources must be managed smartly. MCDA is greatly useful in the management of resources, allocation of resources, selection decisions, quality assessment of resources, optimization of processes, and waste management and guides us on how to intelligently make use of them.

Chen (2000) used Fuzzy TOPSIS for the hiring process of suitable engineers for an IT company. The methodology group decision-making, hence allowing multiple company executives to put in their opinions for hire. Nearly two decades ago when there was still evident confusion in public knowledge about the selection of renewable resources of energy, Kabir & Shihan (2003) used a simple AHP model to determine a realistic source of renewable energy for Bangladesh. The multiple criteria were based on the concerns of cost, practicality, risks, health hazards, and social impact. The study used three alternatives in which the most suitable one was found to be Solar Energy. Similarly, at a time when electric vehicle benefits didn't have much awareness, Tzeng et al. (2005) researched the best fuel alternative for public transport buses than the conventional diesel or petrol. They used a combination of TOPSIS and VIKOR with criteria concerning sustainability, pollution, cost, power output, physical features, feasibility, etc to evaluate the multiple solutions available. The study concluded with the use of electric buses would be the most beneficial alternative while hybrid buses could be used till the industry is prepared for full usage of electric vehicles. These studies are of many evident ways how MCDA has shaped the world as it is today.
Saatly (2001) combined the AHP model with linear programming to make up a guide for the hiring process. The study was able to answer fundamental questions of human resource management such as which designation is to be filled by which applicant while also guiding people with different skill sets doing collaborative work. Gomez-Lopez et al. (2009) employed the TOPSIS method on multiple

procedures for disinfecting the waste water for recycling purposes. The study also included economic parameters which were given high weightage in industrial usage while environmental parameters were given more weightage socially. The chlorination technique was suitable for big industrial purposes, while UV light disinfection was suitable for a smaller scale community usage. Water resource management nowadays is a serious issue among the many environmental concerns, it is obvious water resources are limited and must be managed accordingly. Tian et al. (2009) provided a guide to the pricing of water resources. The study uses a Fuzzy AHP Technique to provide an analysis of water resources based on water quality, consumption, requirements, and environmental factors to segregate the water resources available into five groups, using this the pricing could be done accordingly. Another notable work in water management by Lu et al. (2017) used the simple AHP method on the Huaihe river to determine its water environment carrying capacity based on numerous social and environmental factors. After nearly a decade of data collection, the results showed a surge in capacity while also highlighting the major threats to the capacity.

Huang et al. (2010) proposed a model for saving energy consumption in the working process of thermal power plants. The boiler and steam turbine consume, control unit consumes a lot of energy for its workings, the study used AHP with entropy to calculate the weightage of the energy consumed by parts inside thermal plants, and TOPSIS was applied for evaluation implying the most energy consuming parts. TOPSIS was found useful as the number of criteria doesn’t affect the TOPSIS procedure. Goh et al. (2013) working on electricity allocation applied a combined AHP and TOPSIS approach in a paper pulp mill plant where these methods were used to assign ranks in procedures of the system according to the amount of electricity they consume to design a system such that during low voltage electricity supply the most load consuming process probably could be shut down for continuity. A combination of AHP and TOPSIS methods based on fuzzy set theory was deployed in a study by Kusumawardani and Agintiara (2015) for manager selection in telecom companies. while paying attention to the local values and ethics that are used in the selection process, the criteria were defined based on candidate performance, skillset, education, and accomplishments.

Bian et al. (2018) worked on finding the best site location for off-shore wind farms in China, using the entropy method and AHP method to accomplish that. The wind energy generating farm selection was based on economic budget, variation in wind speed, and some voltage-related electrical factors as most countries transition from the use of non-renewable energy to better sources, a study (Arief et al., 2020) for energy consumption of Malaysia contemplated the use of Nuclear Power Plants and highlight the clear benefits of them over traditional non-renewable sources of energy. The methodology used for comparison was AHP and the results were abiding to shift to hydro plants. A study (Sedghiyan et al., 2021) regarding Iran evaluated the suitable renewable energy resource to help the country transit from non-renewable energy sources to sustainable ones. The study segmented the climate into 5 categories to evaluate the alternatives where the most significant criteria were economic concerns. The study used a mixture of AHP, TOPSIS, and Simple Additive Weighting (SAW) for ranking the energy resources where solar energy emerged as the suitable option.

5.5 Engineering and Manufacturing

Engineering often has to deal with tough decision-making. MCDA has been greatly used in industries for manufacturing, processing, and all-over engineering needs. MCDA is often used to solve problems of designing products, manufacturing processes, automation, quality checks, and risk analysis.

Group decision-making is usually preferred in large-scale organizations where multiple stakeholders or managers collectively make a decision that would be difficult for a single person and provides the diversity of multiple opinions in the decision-making process. Lai et al. (2002) used AHP for group decisions amongst engineering experts, the aim was to select a suitable computer software for a multi-media-related enterprise where the major criteria were technical features and handling concerns. Another study in the same year by Zhang et al. (2010) created a group decision support system with the working of fuzzy sets, after developing the suitable algorithm for the system, the study used TOPSIS combined with the system to evaluate the vehicle capabilities which showed that TOPSIS is useful in group decision making. Chu & Lin (2003) proposed an interesting use of TOPSIS for the selection of robots to automate manufacturing processes in the industry. The study used quantitative criteria such as costs, and technical features as well as qualitative criteria such as communication and interaction between man and robot with the help of fuzzy theory. Milani et al. (2005) use the entropy method for deriving relative priorities since TOPSIS doesn't include a procedure for deriving priorities. The study aims to select suitable materials for the production of gears used in transmission boxes based on their chemical and physical features such as strength and durability keeping safety measures in the procedures as well, the best material was found to be carburized steels, also highlighting how normalization affects the MCDA method.

Taha & Rostam (2012) erected an AHP and Preference Ranking Organization Method for Enrichment of Evaluations (PROMETEE) methodology working of fuzzy sets to create a decision support system for the selection of suitable machining tools, the study was applied to the real-life problem of selecting a suitable computer numerically controlled machine for a manufacturing unit. Athanasopoulos et al. (2009) used TOPSIS working on fuzzy set theory for the prevention of corrosion or immovability in machine parts through the selection of the most functional and beneficial coating materials available. The process concerned itself with engineering requirements, economic costs and availability of material MCDA methods are useful in designing process of engineering as well as products as well, for instance, Wang et al. (2010) conducted a study that aimed to design a machine used in the mill plant, the use of Fuzzy AHP greatly increased the efficiency of the machine while showing the trade-offs that each design changes would bring in performance of the machine.

Mechatronics tools involve multiple fields of engineering to make accurate and functional machines, Phaneendra Phaneendra Kiran et al. (2011) segmented the multiple mechatronics system available with programming and then applied TOPSIS to evaluate the optimal mechatronics system while ranking them with the help of graphs. Shidpour et al. (2013) use a mixture of Fuzzy AHP, TOPSIS, and Multi-objective linear programming to guide the process of new product development (NPD), it also focuses on constructing the product design, manufacturing line, and the selection of vendors in the supply chain. The post-result analysis is further done to provide better insight.

Taylan et al. (2014) used the integration methodology of AHP and TOPSIS both working with fuzzy set theory for risk assessment of construction project works. Consideration of risk is an important part of civil engineering of the hazardous construction work, the study used AHP to evaluate relative priorities such as budget, quality, safety, time, and also sustainability to evaluate the least risky construction project. Li et al. (2017) used AHP and a modified variant of AHP to prevent overwork of pumping stations which are engineered for area drainage. The study used the above methodologies to recognize the old pumping stations which are incapable of delivering good efficiency hence that information can be taken into account for a better drainage system analysis.

Setiawan et al. (2020) to evaluate the most beneficial techniques that can be utilized in the charging station for electric mobility, AHP was used to calculate relative priorities or weights depending upon criteria such as charging, time, cost, and battery used, then the best score for alternatives was calculate using TOPSIS method; the best solution was found to be conductive charging. Gani et al. (2021) aimed to promote sustainable development in the medium-sized Indian enterprises and used Fuzzy AHP for finding green indicators that can serve as a parameter and guide for the manufacturing process for these enterprises. Noticeably, “design for a green environment” was the most effective parameter to be taken into consideration for manufacturing. Quantum processors are the new rising technology against silicon-based computing in the current era, Awan et al. (2022) studied quantum computing to figure out the challenges it is facing currently in 2022. Using Fuzzy AHP, the study concluded by recognizing institutional barriers such as policies and technology laws as the major halting of further growth since they try to limit applications of new technology for possible hazardous reasons and public fear, while other reasons being the ambiguous laws of quantum physics and insufficient efforts by organizations.

6. Conclusion

MCDA represents a repertoire of approaches aimed at dissecting multifaceted problems across various dimensions to facilitate enhanced evaluation, a feat unattainable through basic optimization analysis alone. To effectively navigate intricate decision analyses, the swift integration of MCDA into our individual and institutional decision-making processes becomes imperative. Since the 1970s, MCDA has undergone substantial evolution, with its methodologies continuously diversifying and interconnecting to address the need for more efficient analysis in the contemporary era. In recent studies, new mathematical and computational tools have been used with MCDA to examine the problem from several angles. Consequently, a majority of current research endeavors amalgamate various MCDA approaches within a single problem, seeking to obtain more reliable findings, as evidenced by the study. MCDA approaches are becoming more capable of dealing with problems that are sensitive to uncertainties and offering a precise analysis. MCDA approaches can tackle more ambiguous situations by applying fuzzy set theory to replicate real-world ambiguity. With the help of advances in technology and information processing, MCDA approaches can become more data-intensive, making it easier to find the most critical aspects of a problem while filtering out irrelevant data. Because of its flexibility and openness, as well as its modified variants, AHP remains one of the most commonly used methods. AHP is also a valuable method because it can manage decision-element correlation.

TOPSIS is a prominent method for dealing with problems since it can handle a large number of criteria and offers a dependable method for ranking alternatives based on geometric distances. TOPSIS lacks a mechanism for determining relative priorities, whereas AHP provides a reliable procedure for doing so using pairwise comparisons; thus, a methodology that combines the two is an effective MCDA method. This study explored the theory while focusing on the practical side of MCDA, which is the application of MCDA theories to real-world issues, as well as reviewing recent works to keep current. The previous research works discussed here clearly demonstrate how MCDA has aided in the shaping of current world industries as they exist today. MCDA is still evolving and expanding in terms of decision support.

In conclusion, this study highlights the importance of MCDA as a strong decision-making tool in the dominion of interdisciplinary research. By assimilating various procedural, economic, environmental, and social criteria, MCDA appears as a dependable method for handling complex decision-making challenges. The literature-based methodology engaged in this study provides comprehension into the effective use of MCDA, mostly through AHP and TOPSIS models.

The investigation of AHP and TOPSIS methods reveals their extensive application across various industries from 2000 to 2023, highlighting their adaptableness and effectiveness. Real-world uses, depictions from former research and case studies, contribute to the empathy of the real-world insinuations and success stories allied with MCDA methodologies.

Furthermore, the delineation of MCDA submissions into specific sectors- supply chain, healthcare, business, resource management, and engineering & manufacturing- provides a structured overview of the versatility of MCDA in addressing distinct decision contexts. This study not only contributes to the theoretical understanding of MCDA but also highlights its practical implications, offering valuable insights for researchers, practitioners, and decision-makers across various domains. The integration of MCDA methodologies, particularly AHP and TOPSIS, stands as a testament to its enduring relevance and applicability in navigating the complexities of decision-making in diverse fields over the past two decades.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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