ΣΤΡΑΤΙΩΤΙΚΗ ΣΧΟΛΗ ΕΥΕΛΠΙΔΩΝ
Τμήμα Στρατιωτικών Επιστημών

ΕΛΛΗΝΙΚΗ ΔΗΜΟΚΡΑΤΙΑ
ΔΙΙΔΡΥΜΑΤΙΚΟ ΔΙΑΤΜΗΜΑΤΙΚΟ
ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ
ΑΚΑΔΗΜΑΪΚΟΥ ΕΤΟΥΣ 2022-23
ΣΧΕΔΙΑΣΗ & ΕΠΕΞΕΡΓΑΣΙΑ
ΣΥΣΤΗΜΑΤΩΝ (SYSTEMS ENGINEERING)

(ΠΔ 96 /2015/ΦΕΚ 163Α'/20.08.2014)

ΠΟΛΥΤΕΧΝΕΙΟ ΚΡΗΤΗΣ
Σχολή Μηχανικών Παραγωγής & Διοίκησης

MASTER THESIS

Overview of Artificial Intelligence Touchpoints with Multi-Criteria Decision Analysis

Submitted in fulfilment of the requirements for the Master of Science (M.Sc.) degree of Operational Research, Analytics & Decision Making,

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May 2023

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Keywords

Keywords: Decision Support Systems, Collective Intelligence, Artificial Intelligence, Multicriteria Analysis, Group Decision Making, Multi-Criteria Decision-Making Models

Abstract

The integration of artificial intelligence (AI) in multi-criteria decision analysis (MCDA) and vice versa has been an increasingly active area of research in recent years and has become an interesting topic to researchers who work in the Data Science field. The development of AI technologies has the potential to significantly alter how businesses and organizations now operate and we study how they affect Decision Making in the operational field.

This literature review aims to examine the connection points between AI and MCDA and to provide an in-depth presentation of the contribution of AI in the field of Decision Making. Business managers, technology engineers, developers, analysts and implementers of policies must implement Multi-Criteria Decision Making (MCDM) Models to select their final decisions among all the available alternatives and criteria therefore the establishment of new AI technologies in the Decision-Making field is of high interest.

The methodological approach of the thesis's report is based on valid bibliographic sources analysis. A thorough literature search was done utilizing both electronic databases and manual searches of conference proceedings, books and journals. The review is structured around three main topics: the use of AI techniques for MCDA, the integration of MCDA and AI for decision-making, and the ethical implications of combining AI and MCDA.

The review's key findings show that AI technologies, Decision Making Models, and Information Systems, may be successfully integrated with MCDA to enhance decision-making outcomes. Machine learning algorithms may be utilized to optimize the process of analysing many capabilities based on multiple criteria, and AI-powered decision support systems can give decision-makers with invaluable help.

This analysis concludes that the integration of AI technologies with MCDA has the potential to considerably improve the efficacy and efficiency of decision-making procedures. To fully comprehend the possibilities of this integration and determine the most effective methods for using AI technology in MCDA, more study is required. Finally, another key finding is that the unique viewpoint that human experience and knowledge offer to decision-making cannot be replaced by AI models alone. This involves an awareness of the situation's background and complexities, as well as the capacity to weigh intangible issues such as ethical and societal considerations.

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Acknowledgements

I would like to express my sincere appreciation to the following individuals and organizations who have contributed significantly to the completion of this master's thesis:

First and foremost, I am deeply grateful to my supervisor, Nikolaos Matsatsinis, for his invaluable guidance, expertise, and continuous support throughout the research process. His insightful feedback and constructive criticism have been instrumental in shaping the direction and quality of this thesis.

Lastly, I would like to thank my family and friends for their unwavering encouragement and understanding throughout this challenging academic journey. Their love, support, and belief in my abilities have been my constant motivation.

Chapter 1: INTRODUCTION

In recent years, the field of multi-criteria decision analysis (MCDA) has witnessed a significant growth in its application across various domains. MCDA methods aim to provide decision-makers with a systematic framework for evaluating complex alternatives based on multiple conflicting criteria. As the complexity and diversity of decision problems continue to increase, there is a growing recognition of the potential of artificial intelligence (AI) techniques to enhance the effectiveness and efficiency of MCDA methods and vice versa.

This master thesis aims to investigate the prevalence, relationships, effectiveness, future development, and potential applications of AI techniques in MCDA. By addressing certain research questions, this study aims to provide a comprehensive understanding of the current state of AI techniques in MCDA, their impact on decision-making processes, and potential avenues for future advancements. The findings and recommendations from this research can potentially inform practitioners, researchers, and policymakers on leveraging AI techniques to optimize decision-making processes in various domains.

Overall, this master thesis serves as a valuable contribution to the existing literature on MCDA and AI, shedding light on the synergistic relationship between these two fields and their potential to revolutionize decision-making practices.

Chapter 2: DECISION ANALYSIS

2.1 INTRODUCTION TO DECISION ANALYSIS

2.1.1 DECISION ANALYSIS THEORY

The rational choice theory is a collection of principles that aid in the comprehension of economic and social behaviour. The idea posits that a person will do a cost-benefit analysis to evaluate if a choice is suitable for them, and it proposes that an individual's self-motivated rational actions will contribute to the improvement of the economy. Individual behaviour can be assumed to be rational in a variety of domains, including management, economics, political science, sociology, and philosophy.

The fundamental premise of rational choice theory is that the decisions taken by individual individuals will affect aggregate social behaviour. The idea also presupposes that individuals have preferences among the various options. The assumption is that these preferences are complete and transitive. Individuals are deemed complete if they are able to indicate their preferred option (i.e. individual prefers A over B, B over A or are indifferent to both). In contrast, transitivity occurs when a person weakly favours choice A over option B and option B over option C, leading to the conclusion that the individual weakly prefers option A over option C. The rational actor will next do their own cost-benefit analysis based on a range of criteria to identify their optimal course of action. The previous preference between A, B and C is called relation. A relation on a set is said to connected relation if it compares all different pairs of elements of the set in one way or the other, and it is referred to as highly connected if it relates all pairs. As shown in the section on nomenclature, the language for these features is inconsistent. This concept of "total" should not be confused with a total relation in the sense that for any $x \in X$, there exists a $y \in X$ such that $x R y$. (Matsatsinis, 2022)

Total orders are partial orders in which any two items are similar; that is, the order connection is linked. Similarly, a linked strict partial order is a strict total order. A relation is entire only if it is both partial and strongly related. A relation has a strict total order if and only if it has a strict partial order and is directly related. Never can a strict entire order be tightly related (except on an empty domain).

2.1.2 SUBJECTIVE EXPECTED UTILITY THEORY

As with most of the theories, utility theory has various scientific goals, which are outlined below. Started with applications in economic theory, utility theory plays a major role in the decision making science of organisations and businesses. A primary objective is the explanation of observed economic phenomena, i.e., addressing why questions such as "Why are diamonds normally more expensive than water?" Why does the demand for goods often, but not always, decline as their prices rise? Why do people of all economic levels purchase insurance? A second objective is to offer an accurate account of the observable economic processes, in the sense that the theory attempts to match the available facts. In principle, descriptive validity is independent of explanation, because a theory can adequately describe how objects or people act without explaining why. A third objective is the prediction of unobserved occurrences, such as the forecast of the effects of a rise in the price of a commodity on its demand. This latter statement has, however, gone out of usage, and these three objectives are now jointly referred to as the descriptive purposes of economics. Typically, descriptive objectives of utility theory are contrasted with normative objectives, such as assessment, counsel, and action. In terms of assessment, the optimal behavior of an individual is determined by the behavior that maximizes his or her utility. Consequently, utility theorists assess a particular action as optimum or, as they began to describe it in the 1950s, rational if it maximizes utility. On the basis of this concept, utility theory may also advise individuals on how to behave, specifically, to maximize their utility. If a particular scenario, such as a specific resource distribution, does not maximize the utility of one or more persons, then utility theory may advise ways to act and improve the condition. Scientists concerned with the explanation of economic phenomena, such as exchange rate, price, demand, supply, and market equilibrium, and paid little attention to data fitting or prediction. Marshall was similarly concerned in evaluation and, to a lesser extent, policy action, but on the scale of societal welfare as opposed to individual utility. Concerning utility measurement concerns, there is a substantial distinction between description and prediction on the one hand and explanation on the other. In actuality, utility theory can be descriptively or predictively true even if utility is only indirectly assessed. Consider the basic example in which it is assumed that a specific relationship exists between the non-measurable utility U and a measurable quantity, such as price p= F(U). On the basis of the existing data on p, we may indirectly measure specific values of U and assert that the model p = F(U) adequately describes the issue-at-hand. Using the acquired indirect measures of U, we may then forecast certain unobserved values of p, i.e., some prices. If, when prices are ultimately observed, we discover that the predictions of the model p = F(U) are accurate, we may assert that it is predictively valid. Notably, the above model calibration is independent of the epistemic position of utility interpretation. In other words, the calibration exercise may be conducted based on whether one is mentalist or instrumentalist about usefulness. However, explanations are more complicated. If we believe that utility explains price, we cannot assess utility only based on price without engaging in circular reasoning. One way out of this circularity would be to demonstrate that a very basic, non-unit-based method of measuring utility is conceivable and adequate for explaining pricing. This solution type corresponds to the ordinal method to utility analysis. (Moscati, 2018)

Individual preferences are the basis of utility theory's views. It is a hypothesis posited in economics to explain the behavior of humans based on the premise that people can consistently rate their options according to their preferences. Each individual will exhibit distinct preferences, which appear to be hard-wired into each individual. Thus, we might conclude that the preferences of people are innate. Any theory that attempts to account for preferences must inevitably be an abstraction based on certain assumptions. Utility theory is a positive theory that attempts to explain observable individual behavior and decisions. In the field of economics, it is crucial to distinguish between normative and positive features of a theory. Some individuals think that economic theories ought to be normative, i.e., they ought to be prescriptive and tell people what to do. Others argue, frequently convincingly, that economic theories are intended to provide explanations of observable market agent behavior, and are hence positive in this sense. This contrasts with a normative theory, which advises that individuals should conduct in accordance with its prescriptions. Rather, it is only after watching the decisions individuals make that we may draw conclusions about their preferences, given that the theory itself is positive. When we impose certain constraints on these preferences, we may characterize them analytically using a utility function — a mathematical formulation that ranks the individual's choices in terms of the satisfaction provided by various consumption bundles. Thus, based on the assumptions of utility theory, we may suppose that people behaved as if they had a utility function and acted accordingly. Therefore, the fact that a person is unaware of his or her utility function or even rejects its existence does not invalidate the idea. Using trials, economists have deciphered the utility functions of individuals and the behavior behind their utility. (Moscati, 2018)

Assume that a person encounters a collection of consumption "bundles" to begin. We believe that people have distinct preferences that allow them to "rank order" all bundles based on their attractiveness, i.e., the degree of satisfaction each bundle shall bring to each individual. This preference-based ranking indicates that the theory has ordinal usefulness, as it is meant to examine relative degrees of satisfaction. As previously said, absolute satisfaction is condition-dependent; hence, the theory cannot have cardinal value, or utility that may express the absolute amount of satisfaction. To illustrate this idea, consider that consumption bundles consist of food and clothes for a week in all possible combinations, i.e. food for half a week, clothing for half a week, and all other combinations. Consequently, the following assumptions are made in utility theory:

- Completeness: Individuals are able to sort all potential bundles in ascending order. Rate ordering suggests that the theory posits that, regardless of how many permutations of consumption bundles are presented to an individual, each individual can always rank them according to their preferences. In turn, this implies that individuals are able to compare and rate the satisfaction provided by each bundle. In our example, a week's worth of food and clothes can be compared against a week's worth of food alone, a week's worth of clothing alone, or any combination thereof. This trait, whereby an individual's preferences allow him or her to compare any given bundle with any other bundle, is known mathematically as the completeness property of preferences.

- More-is-better: Assume a person wants to consume bundle A rather than bundle B. Then, he is given with a new bundle that has more of everything in bundle A, denoted by A where = 1. The more-is-better hypothesis states that individuals prefer A to A, which is in turn preferred to B, but also A itself. Using our example, if one week of food is favored over one week of clothes, then two weeks of food is favored over one week of food. The assumption that more is better is termed the monotonicity assumption on preferences in mathematics. There is always the possibility of arguing that this assumption commonly fails. It is not difficult to envisage a person with a full stomach refusing extra food. However, this condition is straightforward to remedy. Suppose the individual has the option of donating the surplus food to another individual or organization of his or her choosing. Even if the individual has had enough food, he or she will still like to consume more. Consequently, under the monotonicity assumption, a hidden property permits the cost-free disposal of any bundle's surplus quantities.

- Convexity: The mix-is-better assumption is referred to as the "convexity" assumption on preferences, or the assumption that preferences are convex. So if an individual prefers $x(=\{x_i\})$ to $y(=\{y_i\})$ and $s(=\{s_i\})$ to $t(=\{t_i\})$ then that person will prefer $\lambda x+(1-\lambda)s$ to $\lambda y+(1-\lambda)t$, for any number λ ,$0<\lambda<1$. In subjective expected utility is the attractiveness of an economic opportunity as perceived by a decision-maker in the presence of risk and it’s assumed not only it is possible to take convex combinations of decisions but also that preferences would be preserved.

- Rationality: This is the most significant and disputed premise underlying utility theory. Under the premise of rationality, people' preferences avoid circularity; if bundle A is preferred to bundle B and bundle B is preferred to bundle C, then bundle A is likewise preferred to bundle C. Under no circumstances does the individual favor C over A. It is likely to be understood why this assumption is contentious. It posits that intrinsic preferences, meaning the rank orderings of bundles of goods, are unchanging independent of context or time.

If one considers preference orderings to be comparison relationships, it becomes easier to build instances in which this assumption is not met. As a result, in "beats"—as in A defeated B in college football—we use the word "against." These are easily discernible connections. For instance, if the University of Crete defeats University of Athens and Athens defeats Thessaloniki, this does not always imply that Crete defeats Thessaloniki. Despite the assumption's limited character, it is a crucial one. It is known as the transitivity of preferences assumption in mathematics. When these four assumptions are true, an individual's preferences can be expressed by a well-behaved utility function. A utility function representation of an individual's preferences can exist without assuming the convexity of preferences. However, this is required if we wish for that function to behave properly. It should be noted that the assumptions lead to "a" function, not "the" function. Therefore, individuals' representations of preferences under a given utility function may not be unique. The existence of well-behaved utility functions explains why comparing the utility functions of different individuals may be pointless (and the notion of cardinal utility misleading). Nevertheless, utility functions are useful tools for describing the preferences of a person, assuming the four conditions are met. Throughout the remainder of this chapter, we will assume that the preferences of every individual can always be represented by a well-behaved utility function. As stated above, a person's level of money determines his or her utility.

Utility theory is founded on the assumption that individuals act as if they make decisions by attributing fictitious utility values to the original monetary values. The decision maker views varying levels of monetary values, translates these values into different, hypothetical terms ("utils"), processes the choice in utility terms (not wealth words), then translates the conclusion back into monetary values. Thus, while we perceive the inputs and outcomes of the choice in monetary terms, the decision itself is made in terms of utility. And considering that utility signifies degrees of satisfaction, individuals behave as though they seek to maximize utility rather than the money quantities seen.

2.1.3 BIASES IN DECISION MAKING

There will undoubtedly be several instances in every workplace where managers or workers must make an informed business choice. To make a decision that will result in the desired conclusion, it is required to use both critical thinking and an evaluation of the effects of many alternatives. During the decision-making process, however, occasionally decision-makers are unknowingly biased. In this article, we define decision-making biases, examine the many types of biases, present strategies for recognizing your personal biases, and offer advice for preventing decision-making biases. When you make decisions based on unconscious processing of past experiences and prior information, you are exhibiting bias. These mental shortcuts can influence your decision-making and result in a decision that differs from what you would make in the absence of biases. Individuals' biases vary based on their own personalities and life experiences. (Marchau et al., 2019)

Self-serving bias – A self-serving bias is one that boosts your self-esteem and makes you feel better about your current decision-making situation. When you have a self-serving bias, you may make decisions that favour you over other workers, consumers, clients, vendors, or the business and its objectives.

Authority bias – Hearing a person in a position of authority give facts or ideas typically instils a certain degree of assurance. Authority bias occurs when you prioritize the input of your authority figures above that of others, despite the existence of more reliable and pertinent facts and viewpoints.

Confirmation effect – Confirmation bias occurs when an individual has pre-existing ideas and gives more weight and importance to information that confirms those opinions. You may, for instance, selectively evaluate evidence that supports your theory, seek for materials that align with your ideas, and reject any information that contradicts your assumptions and beliefs. You run the danger of making a decision that is not in the organization's best interest if you do not examine all of the available facts or examine your convictions.

Framing bias – Anyone providing you with the knowledge you need to make an informed decision will likely express it differently. They may share it with you formally during a planned meeting, send you a report through email, or simply remark pertinent information in passing. Framing bias is when you make a choice based on how the presenter has presented the material, such as assuming that a well-designed presentation is more credible than a plain email.

Anchoring bias – You may already be aware that first impressions are significant for several reasons, but they can also influence your decision-making. Anchoring biases are the result of a person's inherent predisposition to gravitate toward and be affected by the first piece of information they hear. This is the most prevalent form of prejudice when you are under pressure or have little time to make a decision.

Availability bias – The availability bias is based on the first piece of information that quickly comes to mind. For instance, you may recall something from many years ago, imagine it was of great significance, and base your judgments on this recollection. The availability bias also considers the most current information acquired from a reliable source. Those who are susceptible to availability bias may convince themselves that the first notion they've had regarding a choice is the best and, as a result, fail to evaluate alternative possibilities.

Conformity bias – Conformity bias, or making decisions based on what the majority chooses, is one of the greatest obstacles to originality. This might restrict your capacity to generate a different perspective or have an open debate with your coworkers about the decision. Although many employees may possess problem-solving skills, conformity bias might rob them of this ability if they all have the same way of thinking.

Similarity Bias – We favor what is similar to us over what is dissimilar. Similarity biases are particularly evident in judgments about people, including who to employ, promote, and assign to tasks. It arises because people are tremendously driven to view themselves and others in a positive light. We immediately construct "in-groups" and "out-groups" – borders between those we think to be close to us and those who dwell on the outskirts of society. We have a typically positive opinion of our in-group but a dubious or unfavorable opinion of the out-group. Consequently, managers recruit individuals that resemble themselves. To overcome a similarity bias, it is necessary to deliberately discover common ground with individuals who look unlike.

Overconfidence bias – The overconfidence bias can develop when an individual is overconfident in his or her intellect, assumptions, or ideas, sometimes without the information or experience to justify such confidence. Overconfidence bias can drive you to disregard alternative possibilities, take risks with your decisions, and trust that your assumptions are accurate without utilizing other methods to confirm them.

Expediency Bias – We like to act promptly as opposed to patientlyHumans have an innate desire for clarity – to understand what is occurring. A drawback of this requirement is the propensity to make snap decisions without carefully evaluating all the data. When appraising personnel and relying exclusively on a single data point or advice, expedience bias occurs. The solution is to establish a step-by-step process/approach that facilitates the collection of more information. We mistake our perspective for the actual truth due to experience bias.We may be the stars of our own show, but others have a somewhat different perspective on the world. We develop experience biases when we forget this reality. We presume that our perspective on a specific topic or scenario represents the entire truth. To overcome prejudice, we must create processes that allow others to verify our reasoning, offer their viewpoints, and assist us in reframing the current circumstance.

Distance Bias – We favor what is nearby over what is distant. In today's hybrid society, distance prejudices are all too widespread. They occur in meetings when in-room participants fail to solicit feedback from remote colleagues who may be phoning in through video platform.This bias reflects our natural tendency to prefer what is close, whether in physical space, time, or other dimensions. We may counteract distance biases using algorithms that recognize key persons outside of our near vicinity, such as calling on remote colleagues prior to conversing with the room.

Safety Bias – We are more concerned with avoiding loss than pursuing gain. Safety bias is the all-too-human inclination to avoid losing. Numerous research have demonstrated that humans would prefer not to lose money than gaining it. In other words, evil is superior than good.

Feature positive effect – This bias happens when you focus solely on the positive rewards of your actions, rather than assessing the negative repercussions alongside them. This might result in the omission of vital information necessary for making decisions that will help the company achieve its objectives. When you have a limited quantity of time or information, you can trigger the feature's beneficial impact.

Safety biases retard the decision-making process and inhibit healthy kinds of risk-taking. The bias can be mitigated by putting some distance between us and the decision — for example, by visualizing a prior self who has already made the decision successfully — to make those events less emotionally charged.

2.1.4 INDIVIDUAL AND GROUP DECISION MAKING

There are trade-offs between individual and group decision making. Individuals have a larger variety of experiences and ideas than groups, yet groups are susceptible to process losses such as groupthink.

The answer to the question on what is more preferable is contingent on various variables. Taking use of the experiences and viewpoints of a greater number of persons, group decision making provides the benefit of relying on these resources. Therefore, they may be more innovative and result in a more effective conclusion. In reality, groups may occasionally achieve things that individuals could not have accomplished alone. Additionally, groups make the activity more fun for the individuals involved. Lastly, when a group rather than a single individual makes the choice, implementation will be simpler since group members would be invested in the decision. If the group is diverse, better judgments may be made since group members with varied backgrounds and experiences may have different perspectives. Research indicates that diverse, issue-debating management teams create judgments that are more thorough and beneficial to the bottom line in terms of profitability and sales (Simons, et. al., 1999).

Despite its prevalence in businesses, collective decision making has a number of drawbacks. We are aware that groups seldom outperform their top performer. Groups have the capacity to make successful decisions, but they frequently incur process losses. For instance, groups may experience coordination issues. Anyone who has worked on a project with a team of persons will relate to the challenge of coordinating members' work and even attendance at team meetings. In addition, social loafing, or the tendency of certain group members to exert less effort when working together, can be a problem for organizations. Groups may also be afflicted by groupthink, the propensity to avoid evaluating the group's favored views critically. Lastly, group decision-making is more time-consuming than solo decision-making since all members must share their perspectives on many choices. (Zopounidis, 2012)

Consequently, whether an individual or collective choice is desirable will depend on the circumstances. For instance, if there is an emergency and a speedy choice must be made, individual decision making may be chosen. Individual decision-making may also be suitable if the individual in question has all the necessary knowledge and implementation issues are not anticipated. If a single individual lacks the necessary information and abilities to make a decision, if it will be difficult to implement the decision without the participation of others who will be impacted by it, and if the time constraint is moderate, then collective decision making may be more successful.

Among the arguments in favor of individual decision making are the following:

• An individual normally makes decisions quickly, but a group is controlled by several individuals, making decision-making extremely time-consuming. In addition, organizing a group requires a great deal of time.

• Individuals cannot avoid their obligations. They are responsible for their actions and output. It is difficult to hold an individual accountable for a poor judgment inside a group.

• Individual decision-making saves time, money, and effort since individuals often make rapid and rational conclusions, whereas collective decision-making requires a substantial amount of time, money, and effort.

The following are arguments in favor of group decision making:

• A group has the capacity to acquire more comprehensive data than an individual when making judgments;

• an individual relies on his own instincts and perspectives. Because a group contains many members, its diverse perspectives and techniques result in improved decision-making.

• A group uncovers the hidden talent and core capability of a company's personnel.

• An individual will not consider the interests of every member of an organization, but a group will.

2.1.5 OTHER TYPES OF DECISION MAKING

For a company to operate efficiently, choices must be taken continuously. The manner in which decisions are made is crucial to the success of a decision. The leader of a company must determine whether to assume complete control of the decision-making process or to enable other employees to have input. Aside of Individual and Group Decision Making there are additional tools decision makers use such as Top-Down Decision-Making, Bottom-Up Decision-Making, Representative Decision-Making, Quantitative & Qualitative Decision-Making.

Top-down decision-making defines the desired objective or results of a project before identifying the method for achieving those outcomes. This sort of decision-making is frequently associated with a top-down management style, in which the leaders of an organization make the choices and delegate their implementation to other members of the company. Members of an organization frequently have difficulty accepting decisions made from the top down since they are not involved in the decision-making process. Unless the heads of an organization are active in the day-to-day operations of the business on numerous levels, choices made utilizing the top-down model may result in unachievable goals and an excess of work for other members of the organization.

In contrast to top-down decision-making, bottom-up decision-making utilizes a bottom-up strategy. In lieu of declaring goals before deciding the procedure to achieve those goals and leaving organization chiefs to make decisions on their own, the process incorporates input from numerous organizational levels. While the decision is ultimately made by the organization's leaders, this decision is informed by member surveys and departmental discussions on feasible alternatives. In order for bottom-up decision-making to be effective, organizational leaders must evaluate the information they receive with their own professional expertise before making a prudent and well-informed decision. While certain actions may be favored by organization members, the leader may judge that they are not the most prudent course of action.

Representative decision-making transfers decision-making authority from the leadership of an organization to a group that represents several aspects of the organization. In this style of decision-making, at least one person from each department, including the leadership, is selected to participate in the decision-making process. These folks elicit advice on decisions from their coworkers and bring it to meetings where the group evaluates all viable possibilities. After examining all information and ideas, the group reaches a decision by consensus.

In addition to deciding who makes choices in an organization, there are additional factors involved in decision-making. Quantitative decision-making relies on facts and figures to reach a decision. In Qualitative decision-making, experience and other factors, such as staff emotions and consumer connections, are considered. A successful organization will mix the two styles of decision-making to make judgments that are advantageous to the organization's future.

2.2 MULTICRITERIA DECISION ANALYSIS

When there is only one attribute to evaluate, making a decision is relatively straightforward, as in the case of financial products where a monetary amount can represent multiple products; however, many other products and services are characterized by multiple attributes, and determining which one is superior requires evaluating all of the attributes that describe it simultaneously. This sort of problem involving the evaluation of more than two qualities to pick one requires a multicriteria decision-making approach. However, over time, the growth and emergence of new methods and techniques incorporating multicriteria focus has necessitated their classification, as not all of them can be applied under the same conditions and the most important criterion for selecting one is the available and to-be-used information. These approaches used to MCDM may be split into two broad categories: multi-attribute decision making methods (MADM) and multi-objective decision making methods (MODM), where the former techniques are used for discrete problems and the later techniques are used for continuous problems. In discrete situations, the choices are predetermined, and the experts, who are sometimes referred to as judges or decision-makers, evaluate each criterion a priori and indicate its level of relevance. In ongoing issues, however, the options are not predetermined. In these approaches, a set of solutions must be assessed based on a number of constraints. In this instance, experts do an a posteriori assessment. Depending on the information that is initially analyzed, there may be more specific classifications of MCDM methods, such as deterministic if the state of nature in which the alternatives occur is known, stochastic if decision-makers can estimate the probability of an event occurring, or uncertain if the state of nature is unknown and a probability cannot be calculated. Although there are other contemporary classifications, the one described is one of the most frequently recognized, as numerous papers rely on it. The following categorization applies:

• Scoring techniques based on simple mathematical operations that are familiar to all managers are the simplest and easiest to implement. For instance, Simple Additive Weighting (SAW) and Complex Proportional Assessment (COPRAS) employ a normalized value of each criteria and multiply it by a weighted or level that each participating expert in the decision process possesses, but they are only applicable when a criterion must be maximized. COPRAS, on the other hand, may be viewed as an evolved form of SAW and has the benefit that it can be used to maximize or decrease a criterion when needed.

• The distance-based approaches calculate the distance between a given spot and each option. Goal-based programming, for instance, aims to find a solution that meets certain objectives or goals. Through a sequence of constraints, the optimal point must be as near as feasible to a series of predetermined requirements. Other techniques are compromise programming, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) that calculates a distance to an ideal positive and ideal negative alternative, whereas the Multi criteria Optimization and Compromise Solution (VIKOR) method calculates only the distance to an ideal solution [10], and the difference between these methods is the technique used in the normalization process for attributes to eliminate the dims. In addition, they provide the integration of quantitative and qualitative criteria in a single problem, despite the fact that this is sometimes harshly condemned in the academic community. The Analytic Hierarchy Process (AHP), one of the first and most established approaches in this category, has been utilized as a foundation for generating hybrid methods [14]. Later, the Analytic Network Process (ANP) was created as an evolution of the AHP approach since it permits the examination of interdependent criteria [40]. In some texts, these procedures are referred to as the American decision-making school. The outranking techniques are based on a preference connection between a collection of solutions in which each solution demonstrates superiority over the others with regard to a criterion. Their approach is dominated by matrices, which permits the integration of difficult-to-evaluate incomplete and fuzzy information; their most prominent techniques are Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) and Elimination and ChoiceExpressing Reality (ELECTRE) [12]. In some books, these procedures are referred to as the European decision-making school. Lastly, there are utility/value methods, such as Multi-Attribute Utility Theory (MAUT) and Multi-Attribute Value Theory (MAVT), that seek to define the level of satisfaction that different alternatives achieve with respect to a criterion; that is, there is a nominal value to which it is desired to approach, but it is not necessary to maximize or minimize a specific value.

2.2.1 MULTICRITERIA DECISION MAKING

Making decisions is a fundamental human activity at the core of our interactions with the world. We know that people make both excellent and bad judgments, and studies discuss the best effective strategy to aid people in making a "good" decision.

It is possible to classify decisions as organized, semi-structured, or unstructured in order to begin to comprehend how to help them. Structured choice problems possess a known optimal solution, requiring little decision help. A choice involving the shortest path between two places, for instance, can be handled analytically with an accurate answer. Unstructured decision issues lack agreed-upon criteria or solutions and rely on the decision maker's choices. For instance, choosing a partner may be regarded an unstructured choice. In between these two sorts of issues is a large variety of semi-structured problems, which often have certain agreed-upon parameters but still require human input or preferences for a conclusion within a specified set of criteria. For instance, a semi-structured business choice may be whether to grow the company to worldwide markets. Thus, semi-structured choice issues are suitable to decision support, which necessitates the mix of user interaction and analytic approaches to provide alternatives based on criteria and optimal solutions. When artificial intelligence (AI) techniques are used to create options, the resulting systems are known as intelligent decision support systems (IDSS).

Researchers remind us that a full grasp of decision making is necessary for the proper deployment of artificial intelligence and its benefits (Pomerol 1997; Pomerol and Adam 2008). AI seeks to imitate human decision-making in some capacity, and breakthroughs in AI have shown great promise in supporting and enhancing human decision-making, especially in real-time and complicated contexts. This paper will examine studies in decision making and the decision support systems (DSS) that are based on this knowledge, as well as the concurrent use of AI approaches to produce more effective IDSS.

Pomerol and Adam offer a good review of research on human decision making (2008). They contend that reasoning and recognition are interconnected decision-making pillars. Generally speaking, "good" judgments are characterized by reasoning, a uniquely human trait of analysing options and picking a decision based on criteria. Numerous sorts of reasoning may be expressed by analytical approaches and can therefore be incorporated into IDSS. Obviously, not all decisions are analytical. On the opposite end of the spectrum, awareness of stimuli might result in an action or choice that is a learnt reaction without a discernible rationale. However, some progress has been achieved in comprehending replies or judgments in situations where there is no time for critical thought. Interesting study on "recognition-primed decisions" may be found in Klein (1993), who investigated the decision-making processes of firemen and other emergency response workers. Klein's research underlined the importance of pattern-matching in circumstances requiring human experience or fast response. In such situations, decision assistance, if needed, should provide pertinent facts and depend more heavily on human processing. Physiologically, the ability to make decisions resides in the prefrontal lobe of the brain, which is responsible for reasoning. This area's destruction leads to illogical actions and flawed risk assessments (Adolphs et al. 1996; Damasio 1994). Emotion in the brain system is also known to influence decision making, both consciously and subconsciously. Recent research in the field of intelligent decision support systems (IDSS) has revealed the potential to represent affective features such as emotion in decision making (Santos et al., 2011), however the efficient incorporation of emotion in machine reasoning remains a topic for future study. Pomerol and Adam (2008) note that working memory is an essential cognitive capacity for decision making. Since intelligent information processing systems, such as IDSS, are based on computer technologies of memory, symbolic reasoning, and the capacity to record and analyse inputs, they possess the required capabilities to simulate human decision making. The systems suggested for DSS and IDSS are founded on models of human decision making. Savage (1954) proposed an early model of decision making known as the Expected Utility Model or Subjective Expected Utility Model. Savage assumes that if a decision maker begins with a set of states, a set of outcomes, and a preference order of functions from states to outcomes satisfying certain postulates such as transitivity, then the decision maker has a probability on states and a utility function on outcomes to maximize the expected utility for the probabilities (Halpern et al. 2012). Savage's theorem is frequently employed to recommend the action (or choice) that would maximize the expected utility of the decision given a set of known probabilities for previous occurrences. Thus, Savage essentially evolved a model of decision making under uncertainty (Karni 2005). There are several objections to Savage's theorem, most notably the assumption that a decision maker can assess all the outcomes of an action, which requires knowledge of all future occurrences and their related probability. However, one of Savage's most significant contributions was to distinguish events, consequences, and acts (Pomerol and Adam 2008). Simon (1955, 1977, 1997) acknowledged the limits of Savage's theory and developed a Theory of Bounded Rationality in which decision makers are constrained by the information they possess, the time available to make a decision, and their own cognitive resources. Simon's seminal work (1955) offered a behavioral perspective on decision making as a normative process model with three and then four phases (Simon, 1977): (1) Intelligence, (2) Design, (3) Choice, and (4) Implementation.

Decision making is the methodical and rational selection of a single choice from a group of alternatives. A decision-making process is the fundamental, step-by-step decision-making procedure and includes the following steps:

1. Define the decision problem
2. Identify the criteria
3. Identify Alternatives
4. Allocate importance weights to each criterion
5. Score the criteria for each of the alternative
6. Apply the decision rules
7. Evaluate alternatives against criteria
8. Identify the best alternative.

1. Define the decision problem: The choice problem must be well understood by the decision makers. Before making a choice, it is essential to recognize, comprehend, and describe the issue. This method must be able to accurately identify the fundamental causes.

2. Identify the criteria: Goals must serve as the foundation for identifying and establishing criteria that will discriminate among alternatives. A choice issue with a high number of criteria is very useful for producing superior options. A perfect collection of criteria should be functional, significant, and non-redundant.

3. Identify alternatives: Analysis of a small number of options is a crucial component of decision-making. All available options are compared to the selected criteria, and those that do not satisfy the criteria are discarded until only one alternative remains, so reaching the intended outcome.

4. Allocate importance weights to each criterion: The criteria's weights are allocated appropriately, and pairwise comparison is implemented.

5. Score the criteria for each of the alternative: The criteria for each choice are scored to create a matrix, which is then applied to the decision rules.

6. Apply the decision rules: On the basis of the input from criterion weights and scores of criteria from each alternative, it is necessary to apply decision rules in order to find the viable and appropriate alternative.

7. Evaluate alternatives against criteria: After the assessments, the decision making tool may be utilized to rank the alternatives or allows picking a more promising alternative from a group of defined alternatives

8. Identify the best alternative: In the last step of the decision process, evaluation is used to identify the optimal choice, therefore achieving the desired outcome.

Generally speaking, the following rules must be applied in the decision-making science:

• Objectives must be established first must be categorized and prioritized;

• Alternative actions must be developed and evaluated against all objectives;

• The alternative capable of achieving all objectives is the tentative decision;

• The tentative decision is evaluated for additional potential consequences.

• The decisive measures are executed, and extra steps are made to avoid any unfavourable outcomes from becoming issues and resetting both systems (problem analysis and decision-making).

• There are standard procedures that result in a decision model that may be used to establish the ideal production schedule.

• In a conflict scenario, role-playing may be useful for anticipating the decisions made by the persons involved.

The rational choice theory is a collection of principles that aid in the comprehension of economic and social behaviour. The idea posits that a person will do a cost-benefit analysis to evaluate if a choice is suitable for them, and it proposes that an individual's self-motivated rational actions will contribute to the improvement of the economy.

Individual behaviour can be assumed to be rational in a variety of domains, including management, economics, political science, sociology, and philosophy.

2.2.2 DECISION MAKING MODELS

SINGLE-CRITERION DECISION ANALYSIS

Analyzing and comparing options based on a single criterion or objective is the purpose of single-criterion decision analysis. It is typically employed when there is just one aim important to the decision-making process, or when the other objectives may be disregarded or are of minor relevance.

Analysis based on a single criteria comprises finding the decision-relevant criterion and assessing the alternatives based on this criterion. This may be accomplished using a variety of ways, including weighing the criterion, using numerical scales to quantify the significance of the criterion, and utilizing mathematical models to maximize the trade-offs between the options.

One of the primary benefits of single-criteria decision analysis is that it is very easy and uncomplicated, as it entails assessing options based on a single criterion. It is crucial to highlight, however, that single-criterion decision analysis may not be applicable in circumstances requiring the balancing of many competing purposes, as it does not evaluate the trade-offs between distinct objectives. In such situations, a multi-criteria decision analysis may be more suitable.

Overall, single-criteria decision analysis is a valuable method for making judgments when there is only one relevant criterion, or when other objectives may be disregarded or are of minor relevance. It can assist determine the optimum course of action based on the relevant criterion and simplify the evaluation of different courses of action, therefore facilitating the decision-making process.

MULTIPLE-CRITERIA DECISION ANALYSIS

The evaluation of a single criterion, attribute, or perspective that will result in a "optimal" decision is typically insufficient for analyzing the complexity and unstructured nature of real-world decision-making issues. In reality, such a one-dimensional approach is an oversimplification of the true nature of the issue at hand, and it might result in irrational conclusions. Consideration of all relevant aspects associated with the issue concurrently would be a more appealing strategy. One must keep in mind that each decision-maker (DM) has his or her own preferences, experiences, and decision-making policies while handling management difficulties. The discipline of multicriteria decision aid (MCDA) is devoted to the investigation of the aforementioned challenges. MCDA focuses, among other things, on the creation and deployment of decision support tools and procedures to address complex decision issues including many competing criteria, goals, or objectives. It must be highlighted, however, that MCDA approaches and methodologies are not just mathematical models that aggregate criteria to enable automatic optimum decision-making. Instead, MCDA is heavily focused on decision support. In this situation, the DM plays an active role in the decision-modeling process, which is implemented interactively and iteratively until a proposal that suits the preferences and policies of a specific DM or group of DMs is produced. Despite the fact that MCDA has become a prominent and well-recognized topic of operations research, its interactions with other disciplines have also garnered considerable interest. This is evident when one considers the vast array of decision-process-related concerns that the MCDA paradigm covers. Among them are the phases of issue structuring, preference modeling, the building and characterisation of various types of criterion aggregation models, and the design of interactive solution and decision help methods and systems. The diversity of these themes frequently necessitates an interdisciplinary approach.

Multi-Attribute Decision Making

Multi-attribute decision-making (MADM) is the foundation of our method since it permits evaluating options based on numerous criteria and explicitly modeling trade-offs. Multi-attribute decision support systems include of models and approaches that enable decision-makers in selecting one viable choice from a (limited) list of alternatives that satisfy multiple criteria. Thus, an alternative al must be chosen from the collection A = a1,...,an (n IN). In order to do this, the options are ordered according to preferential information. In general, compensatory and noncompensatory techniques are distinguished. While compensatory techniques let a bad performance in one criteria to be offset by a strong performance in another, noncompensatory approaches do not permit this (Guitouni and Martel 1998).

The most prevalent noncompensatory procedures are outranking methods, e.g., PROMETHEE (Behzadian et al. 2010; Brans and Vincke 1985) or ELECTRE (Roy 1991). (Roy 1991). Outranking techniques try to establish outranking relations, which are binary relations between pairs of alternatives that reflect the strength of reasons supporting the claim that ai is at least as good as aj (concordance) and the strength of arguments opposing this claim (discordance) (Roy 1991). Compensatory techniques may be classified into Value System and Disaggregation– Aggregation (D-A) systems. Value system techniques (such as multi-attribute value theory, MAVT) try to establish a value system that aggregates the preferences of decision makers on the criteria based on stringent assumptions on preference relations. They require comprehensive and transitive preference relations and criteria that are comparable (Keeney et al. 1979; Siskos and Spyridakos 1999; von Winterfeldt and Edwards 1986). On the basis of the elicited preferences, a unique (value or utility) function is constructed that aggregates the partial preferences and performances of an alternative on several criteria (Siskos and Spyridakos 1999). D-A techniques, such as the utility additive (UTA) method, analyze the behavior and cognitive style of decision-makers (Jacquet-Lagreze and Siskos 1982, 2001). In the disaggregation phase, a preference model is generated from the evaluations of a small number of reference options by decision-makers. These evaluations are integrated in the aggregation step to value functions (Siskos and Spyridakos 1999). (Siskos and Spyridakos 1999).

Due to its efficacy in strategic decision-making (Bertsch et al., 2006; Chang and Yeh, 2001), we employ MAVT to assess alternatives. In MAVT, the decision-making procedure begins with the problem being restructured from its original intuitive understanding into a form that permits quantitative analysis (von Winterfeldt and Edwards 1986). The phase of problem structuring yields an attribute tree clustering and hierarchically ordering the objectives of the decision-makers (see Figure 3.2). The tree illustrates how the overarching aim is subdivided into increasingly concrete criteria until the level of characteristics is reached. The characteristics are a way to quantify (or quantitatively estimate) the repercussions emerging from the execution of any alternative ai (Stewart 1992). The decision-makers are responsible for determining how the consequences are represented (i.e., how to decide the value of each characteristic under the premise that AI is applied). The attribute tree serves as the foundation for evaluating each choice. To guarantee that the assessment produces an accurate ranking of options, the preferences of the decision-makers are asked. The attribute scores are standardized to ensure that qualities evaluated on various scales may be compared. To this purpose, value functions are provided that map each attribute's score to a number between 0 and 1. The value functions communicate, for each characteristic, the importance of achieving a performance near to the optimum (Keeney et al. 1979). The attribute tree is additionally annotated with weights that allow trade-offs to be made apparent. Each weight for a criterion critj reflects critj's relative relevance relative to all other criteria (Raiffa 2006; von Winterfeldt and Edwards 1986). Finally, the values for each choice are combined into an overall score. MAVT results should not be viewed as an obligatory prescription, but as assistance and direction for the decision-makers (Belton and Stewart 2002). (Belton and Stewart 2002). The majority of the time, decision-maker attitudes will shift during the decision support process (French et al. 2009). Therefore, it is advised that the modeling process be of a dynamic, cyclical character, until a decision model is developed whose form and content are enough to address the issue (Phillips 1984).

Multi-Objective Decision Making

Multi-objective decision making (MODM) is a method for systematically analyzing and comparing alternatives based on numerous competing objectives. It is utilized when conflicting objectives, such as price, quality, time, and performance, must be compromised.

MODM includes the following procedures:

1. Determine the appropriate objectives for the decision-making process. This may entail speaking with stakeholders or doing a requirements analysis to establish the most essential goals.
2. Evaluate the choices in light of the specified goals. This may entail strategies like as weighing the objectives, use numerical scales to quantify the significance of each aim, or utilizing mathematical models to maximize the trade-offs between the objectives.
3. Choose the best option based on the alternatives' evaluations. This may require employing techniques like as sensitivity analysis to investigate the trade-offs between various objectives or scenario analysis to analyze the influence of various assumptions or uncertainties on the choice.
4. Implement the chosen option and monitor its performance to verify it fulfills the predetermined goals.

MODM is a powerful technique for making complicated decisions in scenarios requiring the balancing of numerous competing objectives. It may aid in ensuring that choices are made in a transparent, fair, and inclusive way, as well as in determining the optimal course of action based on all relevant objectives.

MODEL SELECTION & OPTIMIZATION

Model selection and optimization are crucial factors in the creation and use of decision-making models. These procedures involve selecting the optimal model for a particular situation and optimizing the model's parameters to enhance its performance. Model selection is the process of selecting the optimal model from a pool of candidate models based on a set of assessment criteria. There are several model selection strategies, including:

1) Cross-validation is a standard method for selecting a model that includes separating the data into training and test sets and assessing the model's performance on the test set. As the best model, the one with the highest

performance on the test set is selected. Cross-validation is a standard technique for assessing the performance of a machine learning model and picking the optimal model from a pool of candidates. It includes separating the data into training and test sets, utilizing the training set to fit the model and the test set to assess its performance.

There are several forms of cross-validation, such as:

- K-fold cross-validation is the most prevalent cross-validation technique. It includes separating the data into k folds, utilizing k-1 folds for training and the remaining fold for testing. The procedure is repeated k times, with each iteration testing a new fold. To test the model, the average performance over all k folds is employed.
- Similar to k-fold cross-validation, stratified k-fold cross-validation guarantees that the proportions of distinct classes in the data are maintained in each fold. This guarantees that each class is evenly represented in the training and test sets, which is beneficial when the class distribution is uneven.
- Leave-one-out cross-validation is a subset of k-fold cross-validation, where k equals the number of data observations. This means that each observation is utilized as the test set just once, while all other observations are used to train the model. This approach may be computationally intensive, but it can offer a more precise assessment of the performance of the model.
- Cross-validation is a valuable technique for assessing the performance of a model since it offers an estimate of the model's generalization capacity. Cross-validation is essential when picking a model since it helps to confirm that the chosen model is correct and trustworthy, and not just overfit to the training data.

2) Grid search is a model selection technique that searches a predetermined set of hyperparameters for the optimal parameter combination. Grid search

is a model selection technique that searches a predetermined set of hyperparameters for the optimal parameter combination. In machine learning, tuning the hyperparameters of a model to increase its performance is widespread practice.To employ grid search, you must define a collection of hyperparameters to search and a scoring function to evaluate the performance of the model. The grid search method will then train and assess the model using every conceivable combination of the provided hyperparameters, and select the combination that yields the greatest performance based on the scoring function.

3) Ensemble techniques are approaches that integrate numerous models to enhance the model's overall performance. Boosting, bagging, and bootstrapped ensembles are examples. Ensemble methods are machine learning strategies that mix different models to enhance the model's overall performance. There are several ensemble technique kinds, including:

- Boosting: Boosting is a technique of ensemble learning that includes training a series of weak models, then combining their predictions to generate a better overall model. Boosting algorithms function by assigning extra weight to observations that are misclassified by the preceding models in the ensemble, which helps to remedy their mistakes.
- Bagging is a method of ensemble learning that includes training many models on distinct subsets of data and combining their predictions to create a more accurate overall model. Bagging can assist minimize the model's variance, hence improving its performance on fresh data.
- Bootstrapped ensembles: Similar to bagging, bootstrapped ensembles sample the data using replacement to construct the training sets for the various models. This can assist further minimize the model's variance and enhance its performance.

Ensemble approaches can improve the performance of machine learning models, especially when the individual models within the ensemble are poor. However, they might be computationally costly because to the training and evaluation of numerous models.

Model optimization entails fine-tuning the model's parameters in order to enhance its performance. Various optimization strategies, such as gradient descent and simulated annealing, may do this. When selecting and optimizing decision making models, there are various elements to consider, including the model's complexity, the amount of accessible data, and the computational resources necessary. It is essential to establish a balance between model complexity and performance, since highly complicated models may overfit the data and perform badly on fresh data, whereas overly simple models may underfit the data and have poor overall performance.

Model selection and optimization are crucial factors in the creation and use of decision-making models, as they assist to guarantee that the chosen model is accurate, dependable, and successful in resolving the issue at hand.

2.3 TAXONOMY OF MCDA METHODS

Methods of Multi-Criteria Decision Analysis (MCDA) are a diverse collection of techniques used to evaluate and rank alternatives based on multiple criteria. The MCDA methods serve various functions and have distinct characteristics. Some methods are best suited for particular types of problems or decision contexts, while others are applicable to a broader scope of circumstances. The choice of a suitable MCDA method depends on the character of the problem, the preferences of the decision-maker, and the data available. The MCDA taxonomy can be categorized as follows:

Hierarchy-based methods:

a. AHP (Analytic Hierarchy Process)

b. ANP (Analytic Network Process)

Weighted aggregation methods:

a. WSM (Weighted Sum Model)

b. SAW (Simple Additive Weighting)

Distance-based methods:

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

b. F-TOPSIS (Fuzzy Technique for Order of Preference by Similarity to Ideal Solution)

c. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje)

Pairwise comparison and outranking methods:

a. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation)

b. ELECTRE I, II, III (ELimination Et Choix Traduisant la Realité)

c. GRA (Grey Relational Analysis)

Goal-based methods:

a. GP (Goal Programming)

b. BSC (Balanced Scorecard)

Efficiency-based methods:

a. DEA (Data Envelopment Analysis)

Evolutionary optimization methods:

a. MOGA (Multi-Objective Optimization by Genetic Algorithms)

Preference elicitation and evaluation methods:

a. MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique)

b. UTASTAR (UTility Additive STAR)

c. UTA II (The UTility Additive model, version II)

d. UTADIS, UTADIS I (The UTility DIfferential model and Systematic analysis)

e. FUZZY UTA (FUZZY UTility Additive)

Stochastic methods:

a. SMAA (Stochastic Multi-Criteria Acceptability Analysis)

Problem structuring methods:

a. SODA (Strategic Options Development and Analysis)

b. SCA (Strategic Choice Approach)

c. DEMATEL (Decision-Making Trial and Evaluation Laboratory)

Hybrid methods:

a. RST (Rough Set Theory)

The classification of Multi-Criteria Decision Analysis (MCDA) methods is quite comprehensive and covers a wide range of approaches. However, it does not originate from a single source or a specific researcher. Instead, it's a generalized and broad taxonomy that has been derived from various sources within the MCDA research community.

Each of the MCDA methods included in the list has been developed and discussed by various researchers over the years, so attributing the classification to a single researcher is not straightforward. Generally, the taxonomy of MCDA methods varies depending on the specific perspective of the authors, such as their research interest, the particular context of application (e.g., environmental, business, medical), or their theoretical interest (e.g., mathematical, psychological, management). The aim of this classification is to provide an overview of the various MCDA methods and highlight their key characteristics and applications. Some of these methods may belong to more than one group, as the taxonomy is not mutually exclusive.

Hierarchy-based methods:

a. AHP (Analytic Hierarchy Process) - AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It involves decomposing a decision problem into a hierarchy of criteria and alternatives, performing pairwise comparisons of criteria and alternatives, and synthesizing the results to obtain a final ranking of alternatives.

b. ANP (Analytic Network Process) - ANP is an extension of AHP, developed to address situations where there are dependencies and feedback loops among the criteria and alternatives. It uses a network structure to represent the complex relationships and enables a more flexible decision-making process.

Weighted aggregation methods:

a. WSM (Weighted Sum Model) - WSM is a simple and widely used MCDA method that aggregates the performance of alternatives on multiple criteria by assigning weights to the criteria and summing the weighted performances. The alternative with the highest weighted sum is chosen as the best.

b. SAW (Simple Additive Weighting) - SAW is similar to WSM, but it involves normalizing the performance values before weighting and summing them. This ensures that the different criteria are on a comparable scale, leading to more accurate results.

Distance-based methods:

a. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) - TOPSIS is based on the idea that the best alternative should have the shortest distance to the ideal solution and the farthest distance from the negative ideal solution. It involves calculating the relative closeness of each alternative to the ideal solution and ranking them accordingly.

b. F-TOPSIS (Fuzzy Technique for Order of Preference by Similarity to Ideal Solution) - F-TOPSIS extends TOPSIS to deal with uncertain, imprecise, or fuzzy information. It uses fuzzy numbers to represent criteria weights and performance values, and fuzzy distance measures to calculate the closeness to the ideal solution.

c. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) - VIKOR is a compromise ranking method that aims to identify an alternative that is the closest to the ideal solution while considering the balance between the best and the worst performance on all criteria. It calculates the compromise ranking index for each alternative and ranks them accordingly.

Pairwise comparison and outranking methods:

a. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) - PROMETHEE is an outranking method that uses pairwise comparisons of alternatives on each criterion, considering preference functions to determine the strength of preference for one alternative over another. It calculates a net flow of preference for each alternative, which is used for ranking.

b. ELECTRE I, II, III (ELimination Et Choix Traduisant la Realité) - ELECTRE methods are based on the concept of partial comparability of alternatives. They involve constructing an outranking relation by pairwise comparisons of alternatives on each criterion, considering veto thresholds to eliminate alternatives that perform significantly worse on certain criteria. The final ranking is derived from the outranking relation.

c. GRA (Grey Relational Analysis) - GRA is a method that evaluates alternatives based on their similarity or closeness to a reference ideal alternative, considering a grey relational coefficient. It is particularly useful for dealing with uncertain, incomplete, or qualitative information, as it can handle both numerical and categorical data.

Goal-based methods:

a. GP (Goal Programming) - GP is an optimization-based method that aims to find the best alternative by minimizing the deviations from predefined goals or target values for each criterion. It can handle multiple objectives and constraints, and allows for various types of goal preferences, such as prioritized or weighted goals.

Data-driven methods:

a. DEA (Data Envelopment Analysis) - DEA is a non-parametric optimization method used to evaluate the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. It constructs a best-practice frontier by enveloping the DMUs and measures the efficiency of each DMU by calculating its distance to the frontier. In the context of MCDA, alternatives can be treated as DMUs, and their performance on multiple criteria can be considered as inputs and outputs.

Evolutionary and metaheuristic methods:

a. MOGA (Multi-Objective Optimization by Genetic Algorithms) - MOGA is an evolutionary optimization technique that uses genetic algorithms to find a set of optimal or near-optimal solutions for multi-objective problems. It involves searching for a Pareto-optimal set of alternatives, which represents the trade-offs between conflicting objectives. MOGA can be applied to MCDA problems by treating the performance of alternatives on multiple criteria as objectives to be optimized.

Interactive methods:

a. MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) - MACBETH is an interactive decision support method that involves eliciting qualitative pairwise comparisons of alternatives from the decision-maker to construct a value function. It uses a set of categories to represent the differences in attractiveness between alternatives, and it calculates numerical scores based on the decision-maker's judgments. The final ranking of alternatives is obtained by aggregating the scores across criteria.

Fuzzy and imprecise methods:

a. UTASTAR, UTA II, UTADIS, UTADIS I, FUZZY UTA (UTility Additive STAR, The UTility Additive model, version II, The UTility DIfferential model and Systematic analysis, The UTility DIfferential model and Systematic analysis, version I, FUZZY UTility Additive) - These methods are part of the UTA family, which are based on additive utility models for multicriteria decision-making. They aim to elicit a decision-maker's preferences by constructing a utility function that represents their value judgments. The UTA methods can handle imprecise or fuzzy information, and they can be applied to various types of problems, such as choice, ranking, or sorting.

Stochastic and robust methods:

a. SMAA (Stochastic Multi-Criteria Acceptability Analysis) - SMAA is a probabilistic method that deals with uncertainty in criteria weights and performance values. It uses Monte Carlo simulations to estimate the acceptability indices for alternatives, which represent the probability of an alternative being the best according to a randomly selected set of weights. The final ranking is derived from the acceptability indices.

Strategy development and evaluation methods:

a. BSC (Balanced Scorecard) - BSC is a strategic management and performance measurement tool that integrates financial and non-financial indicators to evaluate the performance of an organization. In the context of MCDA, BSC can be used to assess the performance of alternatives based on multiple criteria, such as customer satisfaction, internal business processes, learning and growth, and financial performance. It provides a comprehensive framework for decision-making and enables organizations to align their strategic objectives with their operational activities.

2.4 DECISION SUPPORT SYSTEMS

Decision Support Systems (DSS) are computer-based systems that facilitate decision-making by providing decision makers with pertinent data and analysis tools.

DSSs are intended to aid people or groups of decision-makers in detecting and resolving problems, making informed judgments, and managing difficult circumstances. DSSs provide data, tools, and models to facilitate problem-solving, forecasting, and optimization (Power, 2002). There are various types of DSSs, each with its unique focus and functionality. Additionally, DSSs typically consist of several key components that work together to deliver decision support. (Doumpos et al, 2006)

2.4.1 TYPES OF DECISION SUPPORT SYSTEMS:

Data-driven DSS: These systems primarily focus on the analysis of large datasets to extract valuable insights and patterns. Data-driven DSSs often involve data warehousing, data mining, and OLAP (Online Analytical Processing) techniques to support decision-making (Turban et al., 2005).

Model-driven DSS: Model-driven DSSs utilize mathematical and simulation models to represent complex systems or processes. They enable decision-makers to experiment with different scenarios and evaluate the potential outcomes of various decisions (Power, 2002).

Knowledge-driven DSS: Also known as rule-based or expert systems, knowledge-driven DSSs incorporate domain-specific knowledge and expertise to provide intelligent recommendations. They use artificial intelligence techniques, such as rule-based reasoning and case-based reasoning, to emulate human expertise in a specific domain (Turban et al., 2005).

Document-driven DSS: These systems focus on the management and retrieval of unstructured information, such as documents, images, and videos. Document-driven DSSs help users find relevant information and knowledge to support their decision-making processes (Power, 2002).

Spatial DSS: Spatial DSSs deal with geographical or spatially-related data, such as maps and geospatial datasets. They utilize GIS (Geographic Information Systems) and other spatial analysis tools to support decision-making in domains like urban planning, environmental management, and transportation (Malczewski, 1999).

Group DSS: Also known as Group Support Systems (GSS), these systems facilitate collaboration and communication among decision-makers. Group DSSs provide tools and techniques to support consensus-building, idea generation, and group decision-making processes (DeSanctis & Gallupe, 1987).

2.4.2 COMPONENTS OF DECISION SUPPORT SYSTEMS

Data Management Component: This component is responsible for storing and managing the data required by the DSS. It includes databases, data warehouses, and data marts that store historical, current, and external data from various sources (Power, 2002).

Model Management Component: The model management component encompasses the mathematical and simulation models used in the DSS. It provides tools and interfaces for creating, modifying, and executing these models, allowing decision-makers to analyze different scenarios and evaluate potential outcomes (Turban et al., 2005).

Knowledge Management Component: In knowledge-driven DSSs, this component manages the domain-specific knowledge and expertise used to provide intelligent recommendations. It includes knowledge bases, inference engines, and other AI techniques that facilitate the application of expert knowledge in the decision-making process (Turban et al., 2005).

User Interface Component: The user interface component allows users to interact with the DSS, inputting data, selecting models, and receiving results. It provides a user-friendly and intuitive interface that enables decision-makers to access and use the various functionalities of the DSS effectively (Power, 2002).

Chapter 3: ARTIFICIAL INTELLIGENCE

3.1 INTRODUCTION TO AI

In 1955, John McCarthy, a professor at Stanford, coined the term artificial intelligence (AI), which he defined as "the science and technology of making intelligent machines" (Rajaraman, 2014). Some experts contend that the nature of intelligence may be traced back to the ancient Greeks and other Mediterranean thinkers (Brunette et al., 2009). The Turing Test, devised in 1950, has alternatively been called the birth of artificial intelligence. In July 1956, the term "artificial intelligence" was first used at a Dartmouth College symposium. Initially, artificial intelligence technologies were described as either "top-down" (beginning with higher-level characteristics and actions) or "bottom up" (beginning at the brain level and producing higher-level features) techniques (Brunette et al., 2009). Initially, AI was commonly characterized as the capacity of computers to learn, consider, and study in the same manner as humans; but, over the past 60 years, the notion of AI has broadened to embrace a vast array of technologies and applications (Gao et al., 2021). Even now, with so much AI research being conducted, it is impossible to establish a singular definition of AI. Thus, researchers must develop AI applications while also generalizing its essence.

An AI system performs by collecting and interpreting data using "sensors" that help determine the system's environment, thinking about that environment or processing information based on the sensor data, determining the best course of action, and acting accordingly, using "actuators" and potentially altering the environment. AI systems can utilize symbolic rules or analyze a numerical model, and they can also modify their behavior by observing how their actions affect the environment (European Commission, 2021). Based on their capabilities, AI methodologies and subdisciplines may be split into two categories: (1) reasoning and decision making systems and (2) learning and perception. The following table demonstrates AI domains and subdomains.(Černevičienė, 2022)

AI DOMAIN	AI SUBDOMAIN
Reasoning	Knowledge representation
	Automated reasoning
	Common sense reasoning
Planning	Planning and Scheduling
	Searching
	Optimisation
Learning	Machine learning
Communication	Natural language processing
Perception	Computer vision
	Audio processing
Integration and Interaction	Multi-agent systems
	Robotics and Automation
	Connected and Automated vehicles
Services	AI Services
Ethics and Philosophy	AI Ethics
	Philosophy of AI

Real-world applications of artificial intelligence are continuously expanding. However, the application of AI may be restricted in five practical ways. The first constraint is that training data must be labeled. Machines cannot learn independently under supervision; they must be instructed. This means that individuals must spend time labeling and categorizing the training data required by AI systems. The second restriction of AI is the need for relatively huge data sets. One-shot training, wherein an artificial intelligence model is pre-trained on a set of data and may subsequently learn from a small number of real-world samples, is a method for eliminating the requirement for massive data sets. Thirdly, it is usually challenging to comprehend the outcomes of big, complicated neural network systems. The fourth barrier, the difficulty of generalisation, may be circumvented by transfer learning, wherein an AI model is trained to utilize what it has learnt in doing one task to learn how to execute another. The existence of biases in data and algorithms, which might be difficult to overcome, is the sixth constraint (Bughin et al., 2018). The expanding influence of AI on the environment and society recommends that discourses, social dialogues, and the usage of AI technology should be founded on shared principles, consistent with current management practices and social ideals proven via discussion and study. Sometimes, AI regulation assumes the role of legislation. However, the legislation is not the only method of AI regulation (de Almeida et al., 2021). Mistrust prevails in society over the numerous "smart" solutions given everyday by AI, including issues about intellectual property, security, and privacy linked with a wide range of medical robots, drones, autonomous cars, and other AI applications.

3.2 TAXONOMY OF AI METHODS

This taxonomy of AI techniques provides an overview of some of the most prominent methods and approaches in the field. Despite the fact that different researchers usually classify differently each AI technique, we followed the AI taxonomy as follows: Machine Learning, Deep Learning, Reinforcement Learning, Natural Language Processing, Computer Vision, Robotics and Control, Evolutionary Algorithms, Swarm Intelligence, Fuzzy Logic, Bayesian Networks, Explainable AI and Cognitive Computing. The components/techniques of each method is further discussed in detail in the literature review part.

Machine Learning (ML)

Machine learning is a subset of AI that focuses on designing algorithms capable of learning from and making predictions or decisions based on data. It is one of the most prominent AI techniques, with applications across various domains, such as finance, healthcare, and marketing. Machine learning can be further divided into three main categories:

a. Supervised learning: In supervised learning, algorithms are trained on labeled data, where the input-output relationship is known. The goal is to learn a function that maps inputs to outputs based on the training data. Common supervised learning techniques include linear regression, logistic regression, and support vector machines.

b. Unsupervised learning: Unsupervised learning algorithms work with unlabeled data, where the input-output relationship is unknown. The goal is to discover hidden structures or patterns within the data. Clustering (e.g., K-means) and dimensionality reduction techniques (e.g., principal component analysis) are common unsupervised learning methods.

c. Semi-supervised learning: Semi-supervised learning algorithms use a combination of labeled and unlabeled data. These techniques leverage the larger amount of available unlabeled data to improve the learning process and enhance the performance of the algorithms.

Different machine learning techniques, such as classification, regression, and clustering, have been devised to address various types of problems, such as classification, regression, and clustering. In this section, we examine prominent machine learning techniques and their variants:

Decision Trees are a form of machine learning model that employs a tree-like structure to represent decisions and their potential outcomes. ID3, C4.5, and CART are widely-used examples of decision tree algorithms. These algorithms vary in their splitting criteria and treatment of continuous attributes, but they all strive to create a tree that classifies input data accurately.

Support Vector Machines (SVMs) are a class of supervised learning algorithms used for classification and regression tasks. They function by locating the optimal hyperplane that divides the data elements into distinct classes. SVM variants include linear, radial basis function (RBF), and polynomial kernels, which determine the classification decision boundary type.

Artificial Neural Networks (ANNs) are computational models that are inspired by the structure and function of biological neural networks. They are composed of interconnected, layered, artificial neurons. Multi-Layer Perceptron (MLP), which employs a feedforward architecture with one or more hidden layers, and Radial Basis Function Network (RBFN), which uses radial basis functions as activation functions in the hidden layer, are two common forms of artificial neural networks.

k-NN is a straightforward and user-friendly instance-based learning algorithm used for classification and regression tasks. The algorithm operates by locating the k training examples closest to a new input and predicting the class or value based on the majority vote or average of the neighbors.

Naive Bayes Classifiers is a probabilistic classifier based on the application of Bayes' theorem and the simplification assumption of conditional independence between features. Despite its simplicity, Naive Bayes performs well in a variety of applications, especially text classification and spam detection.

Linear regression is a fundamental statistical and machine learning technique for modeling the relationship between a dependent variable and one or more independent variables. It assumes that the variables have a linear relationship and estimates the coefficients of the linear equation that best suits the data.

Logistic Regression: Logistic regression is a variation of linear regression that is utilized for binary classification tasks. The logistic function is applied to a linear combination of input features to characterize the probability of an instance belonging to a particular class.

Random Forest is an ensemble learning method that combines the predictions of multiple decision trees to increase accuracy and reduce overfitting. It employs techniques such as bagging and feature randomization to generate trees with complementary strengths.

AdaBoost is an adaptive boosting algorithm that combines numerous weak learners, typically decision trees, to produce a powerful classifier. The algorithm iteratively modifies the weights of the training instances based on the performance of the current weak learner, with subsequent iterations focusing on instances that are more difficult to classify.

Gradient Boosting is an additional boosting technique that creates an ensemble of weak learners, typically decision trees, by optimizing a differentiable loss function. It employs gradient descent to minimize the loss function and iteratively adds new weak learners to the ensemble to enhance the performance of the overall model.

XGBoost is a popular and scalable gradient boosting implementation that has been optimized for efficiency and performance. It incorporates regularization, sparsity-aware learning, and parallelization, making it appropriate for large-scale and high-dimensional data problems.

Deep Learning (DL)

Deep learning is an advanced form of machine learning that uses artificial neural networks to model complex relationships between inputs and outputs. These networks consist of multiple layers of interconnected nodes, allowing them to learn hierarchical representations of data. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks are popular deep learning techniques used in tasks such as image recognition, natural language processing, and time series forecasting.

CNNs are a category of deep learning models designed to analyze grid-like data, such as images. They are composed of convolutional layers that discover local characteristics by applying filters to the input data. LeNet, AlexNet, VGG, ResNet, and Inception are popular CNN architectures that vary in depth, connectivity, and complexity.

RNNs are a form of neural network architecture designed for processing sequences of data. They are equipped with feedback connections that enable them to maintain a concealed state that can store information from previous time steps. Common RNN architectures include Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit (GRU) networks, which both address the vanishing gradient problem prevalent in conventional RNNs and facilitate the learning of long-range dependencies.

GANs are a class of deep learning models that learn to generate new data samples that resemble the input data. They consist of a generator network that generates samples and a discriminator network that evaluates the samples' authenticity. In a game-theoretic framework, the generator and discriminator networks are trained simultaneously. DCGAN (Deep Convolutional GAN), CycleGAN, and Pix2Pix are variants of GANs that have been used for tasks such as image synthesis, style transmission, and image-to-image translation.

Autoencoders are a form of unsupervised deep learning model that compresses input data into a lower-dimensional representation and then reconstructs the original data from this representation. Variational Autoencoders (VAE), which impose a probabilistic structure on the latent space, and Denoising Autoencoders, which learn to reconstruct the original data from corrupted inputs, are examples of autoencoder variants.

Capsule Networks: Capsule networks are a recent development in deep learning intended to address some of the shortcomings of conventional CNNs, such as their sensitivity to viewpoint changes and absence of part-whole relationships. They consist of capsules, which are groups of neurons that learn to represent various parts of the input data, and dynamic routing algorithms that capture capsules' hierarchical relationships.

Transformer models are a type of deep learning architecture that has garnered popularity for their capacity to process and generate sequences of data, especially in natural language processing tasks. Without the need for recurrent connections, they capture dependencies between input elements using self-attention mechanisms. Notable transformer models include BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), T5 (Text-to-Text Transfer Transformer), and RoBERTa, which have achieved state-of-the-art performance on a variety of NLP tasks including question answering, sentiment analysis, and machine translation.

Reinforcement Learning (RL)

Reinforcement learning is a type of machine learning where agents learn to make decisions by interacting with their environment and receiving feedback in the form of rewards or penalties. The goal is to learn a policy that maximizes the cumulative reward over time. RL techniques have been applied to various problems, including robotics, game playing, and recommendation systems. Q-learning, deep Q-networks, and policy gradients are some of the prominent reinforcement learning methods.

Natural Language Processing (NLP)

Natural Language Processing is a branch of AI that deals with the interaction between computers and human language. NLP techniques enable computers to understand, interpret, and generate human language, allowing for applications like text analysis, sentiment analysis, language translation, and chatbots. Some popular NLP techniques include tokenization, stemming, lemmatization, part-of-speech tagging, named entity recognition, and sentiment analysis.

Computer Vision (CV)

Computer vision is a field of AI that focuses on enabling machines to interpret and understand visual information from the world, such as images and videos. CV techniques include image recognition, object detection, and scene understanding, which have applications in areas like autonomous vehicles, facial recognition, and medical imaging. Some popular computer vision techniques include edge detection, feature extraction, template matching, and deep learning-based approaches like CNNs.

Robotics and Control

Robotics and control involve the development of intelligent agents that can interact with the physical world. AI techniques in robotics and control include path planning, obstacle avoidance, manipulation, and multi-agent systems. These techniques enable the creation of autonomous robots, drones, and self-driving cars that can navigate complex environments and perform tasks with a high degree of autonomy. SLAM (Simultaneous Localization and Mapping), inverse kinematics, and control theory are some key concepts in robotics and control.

This field encompasses a vast array of techniques that enable robots to navigate complex environments, manipulate objects, and perform duties independently. Here, we expound on a number of fundamental robotics and control concepts and techniques:

Mapping involves producing a representation of the robot's environment in order to facilitate navigation and interaction. From sensor data such as LiDAR, cameras, and sonar, maps are typically created using techniques like occupancy grid mapping and landmark-based mapping.

Inverse kinematics is the process of determining the joint angles and configurations of a robotic manipulator in order to accomplish the desired position and orientation of the end-effector. This is a fundamental problem in robotic manipulation that is frequently solved by geometric, algebraic, or numerical methods.

Model Predictive Control MPC is a sophisticated control technique that employs a model of the system to predict future states and optimize control inputs over a finite time horizon. This enables more precise and efficient control, taking constraints and anticipated disturbances into consideration.

Simultaneous Localization and Mapping (SLAM): SLAM is a technique that enables robots to simultaneously construct a map of an unknown environment and estimate their position within the map. There are numerous SLAM algorithms, including Extended Kalman Filter (EKF) SLAM, FastSLAM, and GraphSLAM, each with its own advantages and disadvantages.

Path planning is the process of determining feasible and optimal paths for a robot to navigate from its initial position to its final position while avoiding obstacles. Popular path planning algorithms include A* (a graph search algorithm that identifies the shortest path), Rapidly-exploring Random Trees (RRT, a tree-based algorithm for exploring high-dimensional spaces), and Probabilistic Roadmap Method (PRM, which creates a roadmap of sampled configurations and connections).

Hierarchical Reinforcement Learning: Hierarchical Reinforcement Learning is an approach for improving the learning efficacy and scalability of reinforcement learning algorithms by decomposing complex tasks into simpler subtasks. Techniques such as options, MAXQ, and the H-DYNA architecture are used to construct hierarchical policies that are easier to learn and modify.

Robotic Operating System (ROS) is a flexible, open-source framework for the development of robot software. It provides libraries, tools, and conventions for the construction of robot applications, enabling developers to create modular and reusable software components for a variety of robotic platforms.

GRASP (Grasp, Release, Approach, Separate, and Place) Planning: GRASP (Grasp, Release, Approach, Separate, and Place) planning involves identifying feasible and stable grasps for robotic manipulators to take up and manipulate objects. Diverse grasp planning algorithms, including eigengrasp, force closure, and antipodal grasping, have been devised to determine optimal grasps based on object geometry, contact points, and force distribution.

Motion Planning: Motion planning is the process of determining a sequence of robot configurations that allow the robot to travel from its initial state to its goal state while adhering to the environment and kinematic constraints. There are sampling-based algorithms (e.g., RRT and PRM), optimization-based algorithms (e.g., CHOMP and TrajOpt), and search-based algorithms (e.g., A* and Dijkstra) for motion planning.

Robotics simulation entails the creation of a virtual environment to simulate and test the behavior of robots prior to their deployment in the real world. Gazebo, V-REP, and Webots are examples of simulation tools that enable researchers and engineers to develop and test robotic algorithms, control strategies, and hardware designs in a controlled and economical manner.

Evolutionary Algorithms

Evolutionary algorithms are a family of optimization techniques inspired by the process of natural selection. These algorithms, such as genetic algorithms, genetic programming, and differential evolution, are used to find optimal or near-optimal solutions to complex problems by simulating the processes of mutation, crossover, and selection. Evolutionary algorithms have been applied to various optimization problems, including function optimization, machine learning, and game playing. Here, we expound on a number of important evolutionary algorithm types:

Genetic algorithms (GA) are search and optimization strategies that simulate the process of natural evolution. Using genetic operators such as selection, crossover (recombination), and mutation, a population of candidate solutions, represented by chromosomes, evolves iteratively. Individuals with the highest fitness are chosen to reproduce, and the process is repeated until a termination criterion is met. The application of GAs to optimization problems, feature selection, and machine learning has been widespread.

Genetic Programming (GP): Genetic programming is a subset of genetic algorithms that evolves problem-solving computer programs or symbolic expressions. The population of GP is composed of tree-like structures that represent programs or mathematical expressions. The genetic operators are customized to manipulate these tree structures, enabling the development of more complex and adaptable solutions. GP has been utilized in the fields of symbolic regression, automatic programming, and data mining.

Particle Swarm Optimization (PSO) is a population-based optimization technique modeled after the social behavior of bird colonies and fish schools. Each particle in particle swarm optimization represents a candidate solution in the search space. Particles traverse the search space by adjusting their velocities according to their own and their neighbors' optimal positions. This collaborative search procedure enables the swarm to converge on the global optimal solution. Function optimization, neural network training, and combinatorial optimization have all utilized PSO.

Differential Evolution (DE) is a population-based optimization algorithm that employs vector difference to generate trial solutions. Individuals in DE are represented as real-valued vectors, and the algorithm generates new experimental solutions by combining the differences of randomly chosen individuals with the current solution. The trial solution then competes with the existing solution using a fitness function, with the superior solution surviving. DE has been applied to problems involving continuous optimization, constrained optimization, and multi-objective optimization.

Evolution Strategies (ES): Evolution Strategies are a category of evolutionary algorithms designed specifically for real-valued optimization problems. In ES, the population consists of real-valued vectors representing individuals. Mutation and recombination operators are utilized to produce offspring, with mutation typically comprising the addition of a random value from a Gaussian distribution to the current solution. ES have been utilized in engineering, machine learning, and robotics for optimization purposes.

Estimation of Distribution Algorithms (EDA): EDAs are a category of evolutionary algorithms that discover and model the distribution of promising solutions in the search space. EDAs generate new candidate solutions by sampling from the estimated distribution, as opposed to using conventional genetic operators. This method permits a more directed and adaptable search procedure. Combinatorial optimization, machine learning, and constraint satisfaction problems have been solved using EDAs.

Swarm Intelligence

Swarm intelligence is a form of AI inspired by the collective behavior of social insects, such as ants, bees, and termites. Swarm intelligence techniques, such as ant colony optimization and particle swarm optimization, are used for problem-solving and optimization tasks that involve decentralized and self-organized systems. These techniques have been successfully applied to various domains, including route planning, scheduling, and network optimization.

Ant Colony Optimization (ACO) is an optimization algorithm that was inspired by the foraging behavior of ants. In their pursuit for food, ants leave behind pheromones that serve as indirect communication signals directing other ants to the food source. ACO simulates this process by iteratively updating a pheromone matrix that represents the desirability of various search space trajectories. Various optimization problems, such as the Traveling Salesman Problem, vehicle routing, and network routing, have been successfully solved using the algorithm.

The Bee Algorithm is inspired by the foraging behavior of honeybees, which seek for nectar sources and communicate their locations to other bees in the hive via a waggle dance. Using scout bees to investigate the search space and worker bees to exploit promising solutions, the algorithm simulates this behavior. The Bee Algorithm has been applied to numerous optimization problems, such as function optimization, clustering, and scheduling.

The flashing behavior of fireflies, which use bioluminescence to attract partners, inspired the Firefly Algorithm. In the algorithm, brighter artificial fireflies attract brighter artificial fireflies, where luminosity represents the quality of a solution. The movement of fireflies toward livelier fireflies in the search space results in the discovery of superior solutions. Problems such as function optimization, feature selection, and image processing have been solved using the Firefly Algorithm.

Artificial Fish Swarm Algorithm (AFSA): AFSA is inspired by the self-organizing and coordinated movement of fish schools. Based on the principles of attraction, repulsion, and alignment, the algorithm simulates the movement of artificial fish in the search space. AFSA has been applied successfully to a variety of optimization issues, including function optimization, clustering, and path planning.

Bacterial Foraging Optimization (BFO): Bacterial Foraging Optimization (BFO) is an optimization algorithm inspired by the foraging behavior of bacteria, such as Escherichia coli, which search for nutrients via chemotaxis, swarming, and reproduction. The algorithm simulates these behaviors in a population of synthetic bacteria that explores the search space in search of optimal solutions. Problems such as function optimization, control system design, and image processing have been solved using BFO.

The Cuckoo Search Algorithm is based on the brood parasitism behavior of certain cuckoo species, which deposit their eggs in the nests of other birds. This behavior is simulated by the algorithm by generating new solutions through the Lévy flight process and replacing less-fit solutions in the population. The Cuckoo Search Algorithm has been utilized for a variety of optimization problems, such as function optimization, structural design, and machine learning.

Fuzzy Logic

Fuzzy logic is an approach to AI that deals with uncertainty and imprecision in data. Fuzzy logic techniques use fuzzy sets and fuzzy rules to represent and manipulate uncertain information, allowing for more human-like reasoning and decision-making in complex environments. Fuzzy logic has been used in various applications, such as control systems, expert systems, and decision support systems.

Lotfi A. Zadeh introduced it in 1965 as an extension of classical logic, which is based on true/false or 1/0 values. In contrast, fuzzy logic allows for continuous truth values spanning from completely true to completely false, making it more applicable to real-world problems involving ambiguous or uncertain data.

Fuzzy logic is founded on the idea of fuzzy sets, which are an extension of classical sets. In traditional set theory, an element is either a member of a set or it is not. In fuzzy set theory, however, constituents can have variable degrees of membership in a set, ranging from 0 to 1. This enables fuzzy sets to more accurately represent the inherent imprecision and ambiguity of many real-world situations. Fuzzy logic techniques are founded on a set of fuzzy rules for representing and manipulating uncertain data. Similar to conventional if-then rules, fuzzy rules use fuzzy sets to define the conditions and outcomes. ambiguous inference systems are used to make decisions or perform calculations based on ambiguous inputs and rules.

Fuzzy inference systems are comprised of four primary elements:

Fuzzification: In this phase, crisp (precise) input values are transformed into fuzzy values by determining their degree of membership in the relevant fuzzy sets. There are a number of fuzzification techniques, including singleton fuzzification, Gaussian fuzzification, and triangular fuzzification.

Rule evaluation: In this phase, the fuzzy rules are evaluated in light of the fuzzy input values. The degree to which each rule is applicable is typically determined using a logical operator such as "and" or "or" to combine the membership degrees of the input fuzzy sets.

Aggregation: The results of evaluating all fuzzy rules are combined into a singular fuzzy output set. This is typically accomplished by taking the union of the individual rule outputs, which can be accomplished using various techniques such as max-min or max-product aggregation.

Defuzzification: The final stage entails transforming the fuzzy output set back into a clear value that can be used for control or decision-making. There are numerous defuzzification techniques, including the centroid method, the maximum membership method, and the weighted average technique.

Bayesian Networks

Bayesian networks are a type of probabilistic graphical model that represent the relationships between variables using directed acyclic graphs. These networks are used for reasoning under uncertainty, causal modeling, and prediction, with applications in fields like medical diagnosis, risk assessment, and decision support. Bayesian networks provide a powerful framework for integrating domain knowledge with observed data to make inferences and predictions.

Explainable AI

Explainable AI focuses on the development of AI systems that provide clear and understandable explanations for their decisions and actions. This area of AI aims to enhance trust and transparency in AI systems, making them more accessible and accountable to users. Techniques in explainable AI include local interpretable model-agnostic explanations (LIME), Shapley values, and counterfactual explanations, among others.

Cognitive Computing

Cognitive computing encompasses a range of approaches and techniques that aim to create systems capable of simulating human cognitive processes. These systems are designed to interact with humans in a natural and intuitive manner, augment human decision-making capabilities, and adapt to new situations. In this section, we will discuss several key types of cognitive computing systems, including expert systems, case-based reasoning, rule-based systems, and intelligent agents.

a. Expert Systems: Expert systems are computer programs designed to mimic the decision-making abilities of human experts in specific domains. They utilize a knowledge base containing domain-specific rules and facts, as well as an inference engine that applies these rules to make decisions or solve problems. Expert systems have been used across various fields, such as medical diagnosis, financial planning, and fault diagnosis, to provide expert-level guidance and recommendations. A knowledge base, an inference engine, and a user interface comprise the fundamental components of an expert system. The knowledge base includes domain-specific principles, facts, and heuristics gleaned from human experts or other sources. This knowledge basis supports the decision-making capabilities of the system. The quality of the system's recommendations is directly influenced by the extent to which an exhaustive knowledge base is created. Knowledge engineers collaborate with domain experts to collect, represent, and organize knowledge in a format that the expert system can process. It is the responsibility of the inference engine to apply the rules and facts recorded in the knowledge base to derive new information or make decisions. It typically employs forward chaining or reverse chaining reasoning techniques to navigate the knowledge base and infer conclusions based on the input provided. Forward chaining begins with the available facts and applies rules iteratively to derive new facts until the objective is reached. In contrast, backward chaining starts with an objective and searches for a series of rules that, when applied, can lead back to the known facts. The choice of reasoning technique is dependent on the problem domain and knowledge base structure.

The user interface of an expert system is intended to facilitate interaction between the system and its users, enabling users to enter data, pose queries, and receive recommendations. An efficient user interface is essential for the efficacy and widespread adoption of an expert system, as it determines how well users can interact with the system and comprehend its output. Modern expert systems frequently employ graphical or natural language user interfaces to improve the user experience and provide a more intuitive means of communication.

Despite their successes, expert systems encounter a number of obstacles. The difficulty of acquiring, representing, and maintaining domain-specific knowledge is one of the major limitations. As knowledge evolves and grows, maintaining an up-to-date knowledge base becomes a time-consuming and labor-intensive endeavor. In addition, expert systems frequently struggle to deal with ambiguous, incomplete, or contradictory data, which can result in suboptimal or incorrect recommendations. In addition, conventional expert systems rely on fixed rules and heuristics, limiting their capacity to learn and adapt to new situations.

b. Case-Based Reasoning (CBR): CBR is a problem-solving approach that relies on past experiences or cases to find solutions to new problems. In CBR, a system maintains a database of previously solved cases, and when faced with a new problem, it searches for similar cases in the database. It then adapts the solutions from these similar cases to create a solution for the new problem. CBR has been applied in various domains, such as medical diagnosis, customer support, and legal reasoning.

Typically, the CBR procedure consists of four stages: retrieve, reuse, revise, and retain. In the retrieval phase, the system explores its case database for cases that are similar to the current problem. The case database is a collection of previously solved problems and their corresponding solutions. Typically, similarity between cases is measured utilizing distance metrics such as Euclidean distance, cosine similarity, or domain-specific similarity measures. To efficiently identify relevant cases, the retrieval procedure may employ indexing techniques and search algorithms, such as k-nearest neighbors or nearest neighbor search.

During the reuse phase, the system modifies the solutions from the previously retrieved cases to produce a solution for the new problem. This process of adaptation may involve basic modifications, such as the substitution of certain elements, or more complex transformations, such as the application of techniques for analogous reasoning or machine learning. The quality of the adapted solution is frequently contingent upon the degree of similarity between the new problem and the retrieved cases, as well as the efficacy of the employed adaptation techniques.

In the revision phase, the system assesses the proposed solution to determine its applicability to the current problem. This evaluation may entail simulations, experiments, or expert feedback in order to assess the performance of the proposed solution and identify potential problems. If the proposed solution is deemed insufficient, the system may return to the retrieval or reuse phases to generate alternative options. The revision procedure ensures that the final solution to the new problem is both feasible and effective.

In the final phase, retention, the system incorporates the new problem and its solution into its case database. This process includes representing the new case in a consistent format, indexing it for efficient retrieval, and possibly updating existing cases to reflect the new information. Retaining new cases enables the CBR system to continuously learn and enhance its performance, adapting to new situations and expanding its body of knowledge.

c. Rule-Based Systems: Rule-based systems are a type of cognitive computing system that relies on a set of predefined rules to make decisions or solve problems. These rules, usually expressed as IF-THEN statements, capture the relationships between different elements in a domain and encode expert knowledge. Rule-based systems are used in various applications, such as natural language processing, expert systems, and business process automation.

A rule-based system is comprised of three primary elements: a rule base, an inference engine, and a working memory. Representing domain-specific knowledge, the rule base comprises a collection of IF-THEN rules, also known as production rules. Each rule consists of a conditional portion (IF) and an action portion (THEN). When a rule's conditions are met, the actions specified by the rule are carried out. The rule base functions as the basis for the system's decision-making capabilities and must be constructed with care to ensure accurate and trustworthy recommendations.

The inference engine is responsible for employing the rules contained in the rule base in order to deduce new information or make decisions based on the available data. Typically, it employs forward chaining or backward chaining reasoning techniques to navigate the rule base and derive conclusions. Backward chaining begins with an objective and searches for a series of rules that can lead back to the available facts. The choice of reasoning technique is determined by the problem domain and the rule base's structure.

During the inference process, working memory stores the facts, intermediate results, and conclusions generated. It serves as a transient repository for the data required to execute the rules and deduce new information. The contents of the working memory are updated to reflect the present state of the system's knowledge as the inference engine applies rules.

Various decision-making duties, including medical diagnosis, fraud detection, and process control, have utilized rule-based systems with great success. In the medical field, rule-based systems such as MYCIN have been used to diagnose bacterial infections and recommend treatments. In the financial industry, rule-based systems are used to detect fraudulent transactions and assess credit risk. In the manufacturing industry, rule-based systems have supported process control and fault diagnosis, assisting operators in identifying and resolving problems to enhance system performance.

d. Intelligent Agents: Intelligent agents are software entities that can autonomously perform tasks or make decisions based on their environment, goals, and knowledge. They often possess learning, reasoning, and adaptation capabilities, enabling them to improve their performance over time and deal with complex, uncertain, or dynamic environments. Intelligent agents can be used in various applications, such as personal assistants, recommendation systems, and autonomous vehicles.

Intelligent agents are autonomous software entities that are able to perceive their environment, reason about it, and take action in order to attain particular goals or objectives. These agents are designed to function in environments that are complex, dynamic, and frequently ambiguous, making decisions and interacting with other agents or systems to complete tasks. Intelligent agents have been utilized in numerous applications, such as web search, recommendation systems, robotics, natural language processing, and multi-agent systems.

An intelligent agent's architecture typically includes several modules, including a perception module, a reasoning module, an action module, and a learning module. The perception module is responsible for acquiring and processing environmental sensory data. Depending on the application domain, this data may include various forms of inputs, such as text, images, sounds, or sensor readings. The perception module frequently employs computer vision, natural language processing, and signal processing techniques to extract pertinent features and representations from unprocessed data.

The reasoning module is responsible for digesting perceived data, making decisions, and developing plans or strategies for achieving the agent's objectives. This module may utilize various artificial intelligence techniques, including rule-based systems, case-based reasoning, and machine learning algorithms, to reason about the environment and make informed decisions. The reasoning module may also include decision-making under uncertainty, employing techniques like Bayesian networks or Markov decision processes to account for incomplete or ambiguous information.

The action module is responsible for putting the decisions made by the reasoning module into environment-applicable actions. This module may require interfacing with other systems, controlling hardware devices, or producing responses in natural language or other output formats. Depending on the application domain, the action module may require robotics, natural language generation, or control theory techniques.

The learning module is responsible for enhancing the agent's decision-making skills and knowledge over time. This module may employ supervised learning, unsupervised learning, or reinforcement learning to learn from the agent's experiences and adapt to new situations. The learning module enables intelligent agents to continuously enhance their performance and become more efficient at accomplishing their objectives.

On the basis of their complexity and capabilities, intelligent agents can be categorized into distinct groups. Simple reflex agents, for instance, respond to their surroundings based on predefined rules or heuristics, without maintaining an internal model of the surroundings. On the other hand, model-based reflex agents maintain an internal model of the environment and use it to make more informed decisions. Utility-based agents make decisions based on a utility function that quantifies the desirability of various outcomes, whereas goal-based agents are capable of setting and pursuing specific goals. Lastly, learning agents can enhance their performance through experience-based learning.

3.3 INTELLIGENT DECISION SUPPORT SYSTEMS

Decision Support Systems (DSS) have emerged as indispensable aids for organizations to make informed decisions. DSSs are computer-based information systems that facilitate decision-making by providing data, tools, and models for the analysis of complex and unstructured problems (Power, 2002). There is a growing interest in developing Intelligent Decision Support Systems (IDSS), which enhance the capabilities of traditional DSSs by incorporating artificial intelligence (AI) techniques and methodologies (Turban & Aronson, 2001). As organizations face increasingly complex decision-making challenges and the need to manage large amounts of data, there is a growing interest in developing Intelligent Decision Support Systems (IDSS).

Traditional DSSs have proven their utility in numerous domains, including healthcare, finance, and supply chain management. Offering analytical tools and models for problem-solving, forecasting, and optimization, they have aided organizations in making better decisions (Power, 2002). However, the swiftly changing business environment and the explosion of data have exposed the limitations of traditional DSSs, necessitating the development of more advanced and intelligent alternatives.

IDSSs address these limitations by incorporating AI techniques that enable them to deal with uncertain, fragmentary, and ambiguous information, thereby making them more capable of tackling real-world decision-making problems (Shim et al., 2002). By utilizing AI, IDSSs are able to provide more precise and useful recommendations, resulting in enhanced decision-making outcomes.

One of the most significant advantages of IDSSs over conventional DSSs is their capacity to learn and adapt to shifting environments. IDSSs can dynamically update their knowledge base and models based on new data and experiences (Turban & Aronson, 2001). In contrast, traditional DSSs frequently rely on immutable models and predefined rules. This flexibility enables IDSSs to maintain their relevance and efficacy in the face of swiftly shifting business environments.

Moreover, IDSSs can process and analyze enormous quantities of data more effectively than conventional DSSs. The incorporation of AI techniques enables IDSSs to identify concealed patterns and relationships within data that would be difficult, if not impossible, for traditional DSSs to recognize (Shim et al., 2002). This capability allows IDSSs to generate more insightful and actionable recommendations for decision-makers.

In addition, IDSSs frequently offer a more interactive and user-friendly experience than conventional DSSs. (Turban & Aronson, 2001) AI techniques enable IDSSs to better comprehend user requirements and provide personalized recommendations based on individual preferences and contexts. This approach improves user engagement and satisfaction, resulting in higher adoption rates and more efficient decision-making processes.

IDSSs also facilitate collaboration and communication among decision-makers, which is vital in the contemporary organizational context. By incorporating tools and techniques for group decision-making, IDSSs promote consensus-building and ensure that diverse perspectives and opinions are taken into account during the decision-making process (DeSanctis & Gallupp, 1987). This collaborative approach yields decisions that are ultimately more robust and well-informed.

By employing AI techniques, IDSSs offer enhanced adaptability, data analysis, user experience, and collaboration capabilities. These developments allow IDSSs to address the complex decision-making challenges encountered by contemporary organizations, resulting in improved decision outcomes and enhanced organizational performance.

Intelligent Decision Support Systems (IDSS) combine the strengths of traditional Decision Support Systems (DSS) with artificial intelligence (AI) techniques, such as machine learning, natural language processing, and expert systems, to enhance their decision-making capabilities. Some types of IDSS are:

Knowledge-based IDSS: These systems integrate domain-specific knowledge and expertise to provide intelligent recommendations. AI techniques, such as rule-based reasoning, case-based reasoning, and natural language processing, are incorporated into knowledge-driven IDSS to enhance their decision-making capabilities.

Machine Learning-based IDSS: These systems utilize machine learning algorithms to analyze large datasets, identify patterns, and make predictions. They can adapt and improve their decision-making capabilities over time as they learn from new data and experiences.

Hybrid IDSS: Hybrid IDSS combines multiple AI techniques, such as machine learning, expert systems, and optimization algorithms, to support complex decision-making processes. By integrating different techniques, these systems can handle a wider range of decision-making challenges and provide more accurate and valuable recommendations.

AI-Optimized IDSS: These systems employ AI-driven optimization algorithms, such as genetic algorithms, particle swarm optimization, and simulated annealing, to find optimal solutions to complex problems. AI-optimized IDSS can handle large-scale problems with multiple objectives and constraints, making them suitable for various domains, such as supply chain management, finance, and engineering.

Natural Language Processing-based IDSS: These systems leverage natural language processing techniques to analyze unstructured text data, such as documents, emails, and social media posts. They can extract valuable insights and provide intelligent recommendations based on the analysis of textual information.

Deep Learning-based IDSS: Deep learning is a subset of machine learning that uses artificial neural networks to model complex relationships between inputs and outputs. Deep learning-based IDSS can handle large and diverse datasets, such as images, audio, and video, making them suitable for applications in domains like healthcare, computer vision, and speech recognition.

Multi-Agent IDSS: These systems consist of multiple intelligent agents that collaborate, negotiate, and coordinate to solve complex decision-making problems. Each agent in a multi-agent IDSS can have its own expertise and knowledge base, and they can work together to reach a consensus or find the best solution to a given problem.

These various types of IDSS leverage different AI techniques to enhance their decision-making capabilities, allowing them to address complex challenges more effectively and support decision-making processes in diverse contexts and domains.

3.4 AI USE CASES

AI and MCDM have several applications in the banking, marketing, and health industries.

3.4.1 FINANCE

AI and MCDM may be utilized in finance to aid in portfolio development and optimization, evaluate the creditworthiness of borrowers, detect and prevent financial fraud, analyze and manage financial risk, and aid in financial trading. Some instances include:

- AI and MCDM may be utilized to aid with portfolio design and optimization by analysing and choosing assets based on many parameters, including risk, return, diversity, and liquidity. In 2020, the financial planning software startup Betterment released Betterment Planning, an AI-powered financial planning tool that analyzes an individual's financial status and provides advice for budgeting, saving, and investing. In 2021, BlackRock, the world's biggest asset manager, introduced FutureAdvisor, an AI-powered robo-advisor that gives individualized financial advice to retail customers.
- Credit scoring: Artificial intelligence (AI) and multi-criteria decision making (MCDM) may be used to evaluate the creditworthiness of

borrowers and measure the risk of default by examining numerous parameters such as credit history, income, assets, and debt levels. In 2019, the credit bureau Experian introduced Experian Boost, an AI-powered credit scoring system that analyzes a person's utility and telecom payments to increase their credit score. In 2021, the online lender Kabbage announced the creation of an AI-powered credit underwriting system that analyzes a company's financial data using machine learning algorithms and provides creditworthiness recommendations.

- AI and MCDM may be used to detect and prevent financial fraud by analyzing transactions and discovering abnormalities or trends that may suggest fraudulent conduct. In 2020, JP Morgan Chase announced the creation of an artificial intelligence system called COiN that utilizes natural language processing to evaluate legal papers and extract data, therefore lowering the time required to examine and negotiate contracts.
- AI and MCDM may be used to analyze and manage financial risk by analyzing the probability and effect of various hazards and selecting the most suitable risk-mitigation measures.
- Customer service: In 2021, Bank of America will introduce Erica, an AI-powered chatbot that employs natural language processing to respond to customer inquiries and offer individualized financial advice.
- AI and MCDM may be utilized to aid in financial trading by assessing market circumstances and recommending when to purchase or sell assets. In 2018, Goldman Sachs announced Marcus, an AI-powered trading system that analyzes market data and executes trades using machine learning algorithms.

3.4.2 MARKETING

AI and MCDM can be utilized in marketing to analyze customer data and identify customer segments or groups with similar characteristics, personalize marketing efforts, automate certain aspects of the marketing process, predict customer behavior and identify trends or patterns, and optimize marketing efforts. Some instances include:

- Customer segmentation: AI and MCDM may be used to evaluate customer data and discover client segments or groups with similar characteristics to adapt marketing efforts to specific customer groups. In 2020, Adobe released Adobe Sensei, an AI-powered customer segmentation platform that employs machine learning algorithms to evaluate customer data and generate customised segments for targeted marketing efforts.
- Personalization: AI and MCDM may be used to customize marketing efforts by evaluating consumer data and recommending the most relevant marketing messages or offers for specific customers. In 2018, Amazon announced Amazon Personalize, an AI-powered recommendation system that employs machine learning algorithms to present consumers with tailored product recommendations based on their browsing and purchase history. In 2019, the chatbot platform MobileMonkey introduced Watson, an AI-powered chatbot that leverages natural language processing to converse with consumers and deliver individualized advice and assistance.
- Marketing automation: AI and MCDM may be used to automate various components of the marketing process, including the selection of target audiences, the development of marketing campaigns, and the optimization of marketing budgets. In 2021, the email marketing platform Persado developed an AI-powered email marketing product called Persado AI that optimizes subject lines and email text for optimal engagement using natural language processing
- In order to inform marketing plans, AI and MCDM may be used to forecast consumer behavior and uncover trends or patterns that may signal future client demands or preferences. In 2020, the ad targeting platform Adgo will unveil Adgo AI, an AI-powered ad targeting system that analyzes client data and provides individualized ad recommendations

using machine learning algorithms. In 2020, the social media marketing platform Hootsuite will debut Hootsuite Amplify, an AI-powered social media marketing tool that analyzes social media data using machine learning algorithms and provides tailored suggestions for content and interaction.

- AI and MCDM may be used to optimize marketing efforts by examining the efficacy of various marketing campaigns and selecting the most successful marketing tactics based on several factors, such as reach, engagement, and conversion. In 2021, the content marketing platform Articoolo announced Articoolo AI, an artificial intelligence-powered content creation tool that employs natural language processing to produce original, SEO-optimized pieces based on a specified topic.

3.4.3 HEALTH INDUSTRY

AI and MCDM may be utilized in the healthcare business to aid in medical diagnosis, customize treatment regimens, give clinical decision support, forecast patient outcomes and find trends or patterns, and optimize healthcare resources and procedures. Some instances include:

- AI and MCDM may be used to aid in medical diagnosis by analyzing patient data and recommending the most likely diagnosis based on various factors such as symptoms, test results, and medical history. In 2018, the medical technology startup Enzyme Health introduced Second Opinion, an AI-powered diagnostic tool that employs machine learning algorithms to evaluate medical information and make therapy suggestions.

- AI and MCDM may be used to tailor treatment regimens by assessing patient data and recommending the best suitable treatment alternatives based on many variables, such as efficacy, side effects, and patient preferences. ClinicalTrials.gov released in 2021 an AI-powered clinical trial matching tool that employs natural language processing to examine patient information and match them with pertinent clinical studies.

- Electronic health records: In 2021, Epic Systems, a provider of electronic health records, will deploy a tool called Epic Rover that utilizes natural language processing to extract data from electronic health records and make treatment suggestions.
- AI and MCDM may be used to give clinical decision support to healthcare practitioners by giving pertinent information and alternatives and assisting in the evaluation of the pros and cons of various treatment options. In 2020, the clinical decision support platform Imagen introduced Imagen AI, an AI-powered solution that employs machine learning algorithms to evaluate medical pictures and give diagnosis and treatment suggestions.
- AI and MCDM may be used to anticipate patient outcomes and detect trends or patterns that may signal future health requirements or dangers in order to advise treatment and prevention programs. In 2020, the healthcare analytics business IBM Watson Health will debut Watson for Oncology, an AI-powered predictive analytics platform that employs machine learning algorithms to evaluate cancer patients' medical information and deliver individualized treatment recommendations.
- Telemedicine: In 2020, the telemedicine platform Teladoc Health introduced Livongo, an AI-powered telemedicine service that employs machine learning algorithms to evaluate patient data and deliver individualized health recommendations.
- AI and MCDM may be used to improve healthcare resources and procedures by examining the efficacy of various treatment alternatives and determining the most efficient and effective techniques based on several parameters including cost, quality, and patient satisfaction.

Overall, the employment of AI and MCDM in finance, marketing, and the healthcare business may enhance decision-making and risk management, as well as allow the efficient and effective administration of financial and healthcare resources.

In addition, they may assist the delivery of evidence-based and cost-effective healthcare services, as well as the design of individualized and targeted marketing campaigns and treatment plans that correspond with client requirements and preferences.

In many situations, AI models can give useful data and analysis on the potential outcomes of a choice, but they may be unable to adequately address the ethical implications of such results. AI models may be able to find the most cost-effective treatment choice for a patient in the healthcare sector, but they may not be able to properly examine the ethical implications of that therapy, such as whether it is in the patient's best interest. In these situations, ethical issues must be weighed using human experience and discretion in order to make educated judgments.

AI models can be good at evaluating data and recognizing trends, but they may not be able to properly evaluate the strategic ramifications of various possibilities when developing a strategy. For instance, an AI model may be able to recognize patterns in customer behavior and recommend strategies for targeting specific demographics, but it may not be able to fully consider the long-term goals and objectives of an organization or the potential impact of those strategies on other stakeholders. In such circumstances, human experience and knowledge are required to create and implement successful plans that take into consideration an organization's long-term goals and objectives.

While AI models may be used to automate certain elements of customer service, such as responding to commonly asked questions or directing customer enquiries to the proper department, they may not be able to completely comprehend the context and subtleties of individual customer interactions. For instance, an AI model may not completely comprehend the tone or emotion underlying a customer's request, which might result in misunderstandings or improper answers. In such circumstances, human experience and empathy are required to successfully address consumer demands and give individualized service.

AI models may be used to evaluate and understand legal material, such as case law or legislation, but they may not be able to properly examine the legal context and ramifications of various solutions. For instance, an AI model may be able to identify significant legal precedents for a given case, but it may not be able to properly evaluate the legal concepts or arguments presented by the parties. In such circumstances, human knowledge and competence are required for making informed and legally competent choices.

3.4.4 HUMAN RESOURCES

Artificial intelligence and multi-criteria decision making (MCDM) may be used to evaluate job candidates based on numerous factors, such as education, experience, abilities, and personality. For instance, an AI system may be educated on data on prior successful hiring, and then evaluate fresh prospects using MCDM approaches. This might help organizations make more informed recruiting decisions, and perhaps increase the quality of their personnel.

3.4.5 OPERATIONS MANAGEMENT

AI and MCDM may be used to optimize numerous elements of operations management, such as inventory control and production scheduling. For instance, an AI system may be trained on historical manufacturing process data and then employ MCDM approaches to discover the most effective scheduling and inventory management tactics. This might help organizations save expenses and enhance efficiency.

3.4.6 INSURANCE

AI and MCDM can be utilized to enhance the precision of risk assessments in the insurance sector. For instance, an AI system may be trained on historical insurance claims and policyholder behavior, and then evaluate the risk associated with insuring a particular individual or group using MCDM approaches. This might assist insurance firms with risk management and increase the precision of underwriting judgments.

3.4.7 SUPPLY CHAIN MANAGEMENT

AI and MCDM may be utilized to optimize several areas of supply chain management, including demand forecasting and transportation optimization. For example, an AI system may be educated on data regarding previous demand patterns and transportation routes, and then apply MCDM techniques to discover the most efficient transportation routes and inventory management tactics. This might help organizations save expenses and enhance efficiency in their supply chain operations.

3.5 ETHICAL IMPLICATIONS

In many situations, AI models can give useful data and analysis on the potential outcomes of a choice, but they may be unable to adequately address the ethical implications of such results. AI models may be able to find the most cost-effective treatment choice for a patient in the healthcare sector, but they may not be able to properly examine the ethical implications of that therapy, such as whether it is in the patient's best interest. In these situations, ethical issues must be weighed using human experience and discretion in order to make educated judgments.

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Here are a few instances of the potential abuse of artificial intelligence in decision-making:

If an AI model is trained on a biased data set, it may generate racially biased findings when evaluating job applicants. For instance, an AI model trained on data from a corporation with a history of mostly recruiting white people may be prejudiced towards candidates of other races. This may cause the AI model to propose white candidates over more competent individuals of other races, resulting in prejudice throughout the recruiting process.

Biased risk assessment: Artificial intelligence models are frequently employed in the criminal justice system to forecast the possibility of recidivism; but, if these models are trained on biased data, they may provide biased conclusions that disproportionately affect particular populations. For instance, an AI model trained on data from a criminal justice system that disproportionately targets and punishes people of color may be prejudiced towards these people and advocate harsher punishments or treatment.

AI models may be used to target individuals with individualized marketing; but, if the data utilized to train these models is skewed or manipulated, the adverts may be deceptive or misleading. This may cause customers to make judgments based on inaccurate or misleading data.

AI models may be used to automate the generation and distribution of fake or misleading material on social media platforms. This can be used to manipulate public opinion or propagate disinformation, resulting in individuals and organizations making misinformed or prejudiced decisions.

Chapter 4: LITERATURE REVIEW

In recent years, multi-criteria decision analysis (MCDA) and artificial intelligence (AI) have attracted considerable interest. Both techniques seek to facilitate decision-making in situations with competing aims and criteria. Integration of MCDA with AI approaches can result in more resilient, efficient, and precise decision-making procedures across multiple domains. This work seeks to give a complete literature analysis on the integration of MCDA and AI approaches, concentrating on the potential benefits, problems, and future research prospects.

4.1 GOALS

Goal 1: To identify and analyze the prevalence of various AI techniques used in multi-criteria decision analysis (MCDA) methods.

Goal 2: To examine the relationships between specific AI techniques and MCDA methods.

Goal 3: To assess the effectiveness of AI techniques in enhancing the performance of MCDA methods.

Goal 4: To provide insights into the future development and potential applications of AI techniques in MCDA.

Goal 5: To offer recommendations for the integration of AI techniques with MCDA methods.

4.2 RESEARCH QUESTIONS

Research Question 1: What are the key AI techniques used in MCDA methods, and what is their distribution in the literature?

Research Question 2: How do AI techniques relate to MCDA methods, and are there any patterns or trends in the combination of AI techniques with specific MCDA methods?

Research Question 3: How do AI techniques contribute to the performance of MCDA methods, and what are the advantages and disadvantages of using AI techniques in MCDA?

Research Question 4: Based on the current state of AI techniques in MCDA, what are the potential future developments, and how can these advancements be applied to address real-world problems?

Research Question 5: Considering the trends and patterns observed in AI techniques and MCDA methods, what recommendations can be made to facilitate the effective integration of AI techniques with MCDA methods for improved decision-making?

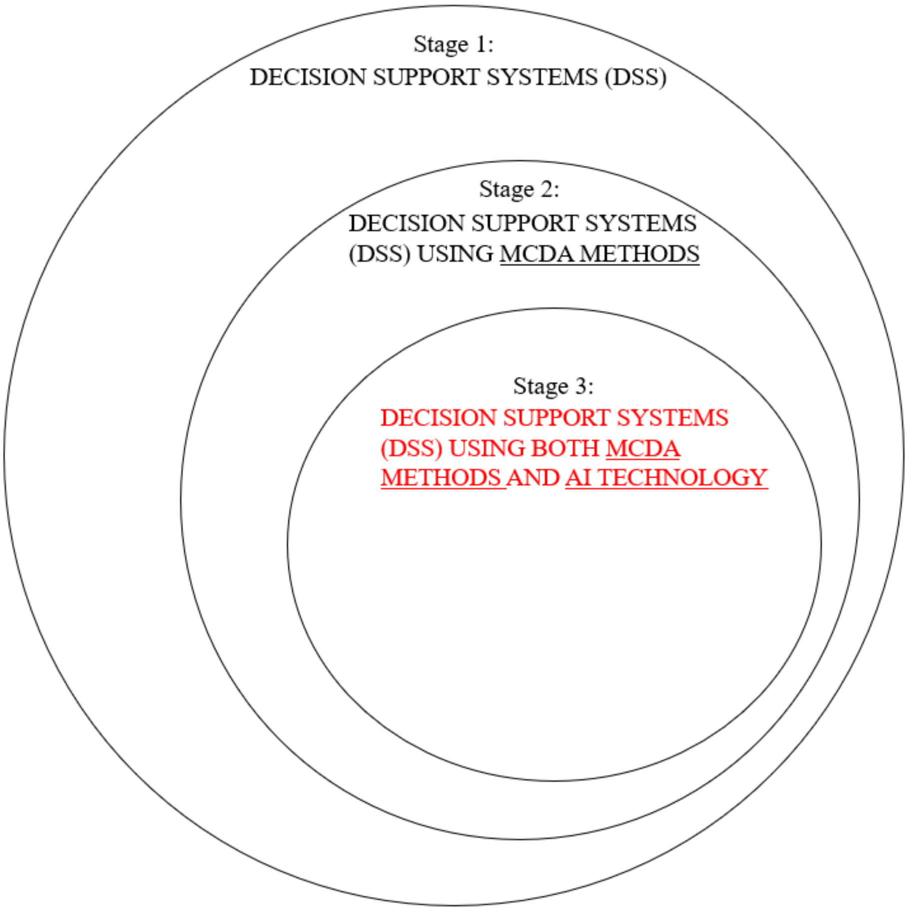
4.3 METHODOLOGY

4.3.1 DATA COLLECTION

Data collection was based on papers with prominent reference on Decision Support Systems (Stage 1), where MCDA methods were used (Stage 2). The collection of data includes the following fields: Authors, Title, Year, Link, Abstract, Indexed Keywords, Author Keywords and Subject Area. In the last stage of our data selection (Stage 3), we filtered our findings to solely include those using AI Methods. For stage 2 the following query was used in Scopus.

“TITLE-ABS-KEY ("AHP" OR "WSM" OR "TOPSIS" OR "PROMETHEE" OR "SAW" OR "GP" OR "DEA" OR "MOGA" OR "GRA" OR "VIKOR" OR "MACBETH" OR "F-TOPSIS" OR "SMAA" OR "BSC" OR "SODA" OR "SCA" OR "DEMATEL" OR "ANP" OR "RST" OR "UTASTAR" OR "UTA II" OR "UTADIS" OR "UTADIS I" OR "FUZZY UTA" OR "ELECTRE I" OR "ELECTRE II" OR "ELECTRE III" OR "ELECTRE TRI" OR "ELECTRE-TRI" AND "artificial intelligence" OR "Machine Learning" OR "Natural Language Processing" OR "NLP" OR "Knowledge Representation" OR "Cognitive Computing" OR "Reinforcement Learning" OR "Deep Learning" OR "Computer Vision" OR "Robotics" AND "DSS" OR "Decision Support System"

OR "Decision Support Systems") AND PUBYEAR > 1988 AND PUBYEAR < 2023"



4.3.2 LIMITATIONS

We limited our review to papers published between 1989 and 2022, based on the following MCDA Methods (Stage 2):

MCDA METHODS	
1. AHP - Analytic Hierarchy Process	AHP
2. WSM - Weighted Sum Model	WSM

3. TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution	TOPSIS
4. PROMETHEE - Preference Ranking Organization Method for Enrichment Evaluation	PROMETHEE
5. SAW - Simple Additive Weighting	SAW
6. GP - Goal Programming	GP
7. DEA - Data Envelopment Analysis	DEA
8. MOGA - Multi-Objective Optimization by Genetic Algorithms	MOGA
9. GRA - Grey Relational Analysis	GRA
10. VIKOR - VlseKriterijumska Optimizacija I Kompromisno Resenje	VIKOR
11. MACBETH - Measuring Attractiveness by a Categorical Based Evaluation Technique	MACBETH
12. F-TOPSIS - Fuzzy Technique for Order of Preference by Similarity to Ideal Solution	F-TOPSIS
13. SMAA - Stochastic Multi-Criteria Acceptability Analysis	SMAA
14. BSC - Balanced Scorecard	BSC
15. SODA - Strategic Options Development and Analysis	SODA
16. SCA - Strategic Choice Approach	SCA
17. DEMATEL - Decision-Making Trial and Evaluation Laboratory	DEMATEL
18. ANP - Analytic Network Process	ANP
19. RST - Rough Set Theory	RST
20. UTASTAR - UTility Additive STAR	UTASTAR

21. UTA II - The UTility Additive model, version II	UTA II
22. UTADIS - The UTility DIfferential model and Systematic analysis	UTADIS
23. UTADIS I - The UTility DIfferential model and Systematic analysis, version I	UTADIS I
24. FUZZY UTA - FUZZY UTility Additive	FUZZY UTA
25. ELECTRE I - ELimination Et Choix Traduisant la Realité, version I	ELECTRE I
26. ELECTRE II - ELimination Et Choix Traduisant la Réalité, version II	ELECTRE II
27. ELECTRE III - ELimination Et Choix Traduisant la Réalité, version III	ELECTRE III
27. ELECTRE III - ELimination Et Choix Traduisant la Réalité, version III	ELECTRE TRI

In Stage 3 we focused our search on findings using the following AI Methods:

Machine Learning (ML)
Deep Learning (DL)
Reinforcement Learning (RL)
Natural Language Processing (NLP)
Computer Vision (CV)
Robotics and Control
Evolutionary Algorithms
Swarm Intelligence

Fuzzy Logic
Bayesian Networks
Explainable AI
Cognitive Computing

For the classification of the papers into each AI Method, AI keyword techniques were tracked using programming language Python based on the following table:

ARTIFICIAL INTELLIGENCE METHODS TAXONOMY
Machine Learning:
Decision Trees (e.g., ID3, C4.5, CART)
Support Vector Machines (e.g., Linear, Radial Basis Function, Polynomial)
Artificial Neural Networks (e.g., Multi-Layer Perceptron, Radial Basis Function Network)
k-Nearest Neighbors (k-NN)
Naive Bayes Classifier
Linear Regression
Logistic Regression
Random Forest
AdaBoost
Gradient Boosting
XGBoost
Deep Learning:
Convolutional Neural Networks (e.g., LeNet, AlexNet, VGG, ResNet, Inception)

Recurrent Neural Networks (e.g., Long Short-Term Memory, Gated Recurrent Unit)
Generative Adversarial Networks (e.g., DCGAN, CycleGAN, Pix2Pix)
Autoencoders (e.g., Variational Autoencoder, Denoising Autoencoder)
Capsule Networks
Transformer models (e.g., BERT, GPT, T5, RoBERTa)
Reinforcement Learning:
Q-Learning
Deep Q-Networks (DQN)
Proximal Policy Optimization (PPO)
Actor-Critic Methods (e.g., A2C, A3C)
Trust Region Policy Optimization (TRPO)
Soft Actor-Critic (SAC)
Monte Carlo Tree Search (MCTS)
Deep Reinforcement Learning
Actor-Critic Methods
Policy Gradient Methods
Multi-Agent Reinforcement Learning
Inverse Reinforcement Learning
Model-Based Reinforcement Learning
Natural Language Processing (NLP):
Machine Translation
Transformer models (e.g., BERT, GPT, T5, RoBERTa)
Sequence-to-Sequence models (e.g., LSTM-based, GRU-based)

Attention mechanisms (e.g., self-attention, multi-head attention)
Word embeddings (e.g., Word2Vec, GloVe, FastText)
Named Entity Recognition (NER)
Sentiment Analysis
Text Classification
Coreference Resolution
Text Generation
Computer Vision (CV):
Image Classification
Image segmentation (e.g., U-Net, Mask R-CNN)
Object detection (e.g., YOLO, Faster R-CNN, Single Shot MultiBox Detector)
Image generation (e.g., StyleGAN, BigGAN)
Optical Character Recognition (OCR)
Pose Estimation (e.g., OpenPose, DensePose)
Image-to-Image Translation
Video Analysis
Robotics and Control:
Mapping
Inverse kinematics
Model Predictive Control (MPC)
Simultaneous Localization and Mapping (SLAM)
Path planning algorithms (e.g., A*, RRT, PRM)
Hierarchical Reinforcement Learning

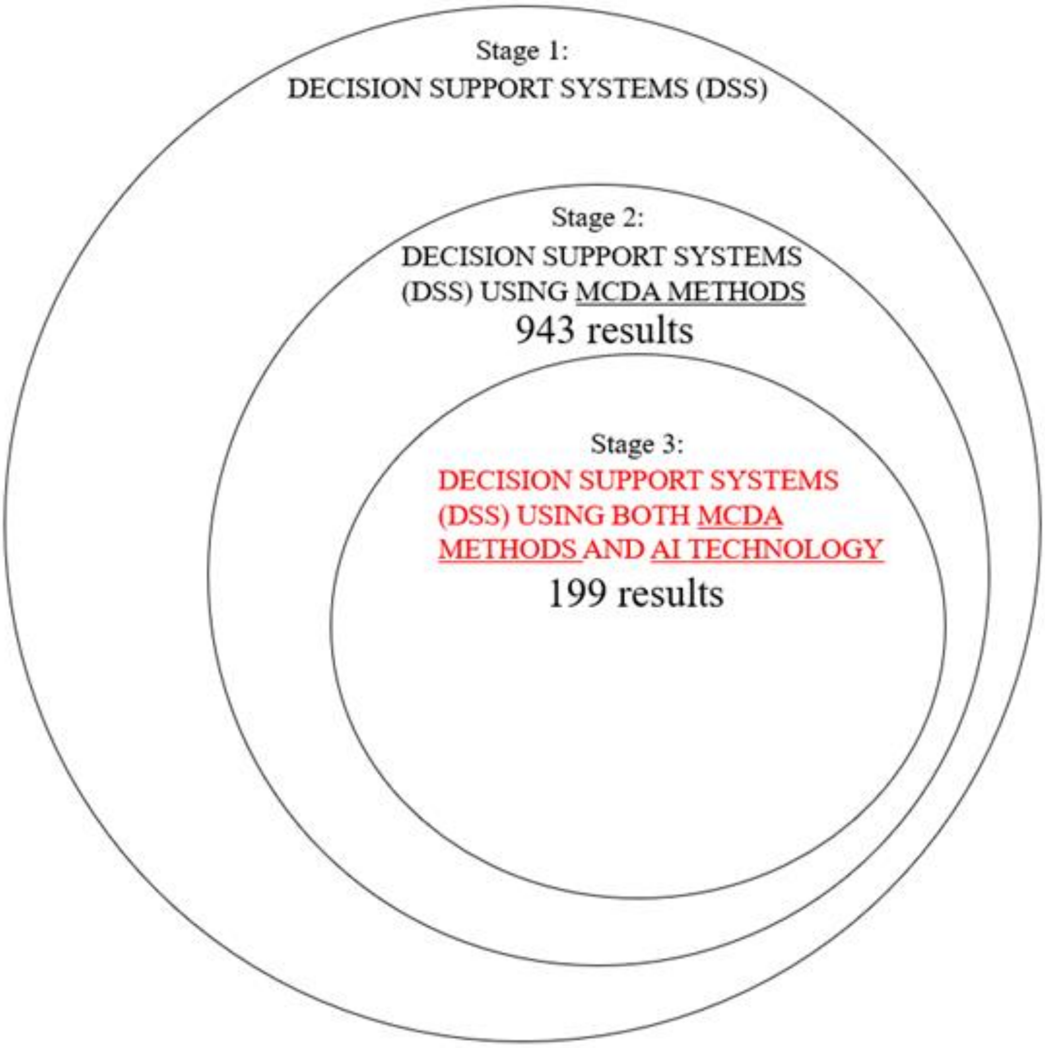
Robotic Operating System (ROS)
GRASP Planning
Motion Planning
Robotics Simulation
Evolutionary Algorithms:
Genetic Algorithms
Genetic Programming
Particle Swarm Optimization
Differential Evolution (DE)
Evolution Strategies (ES)
Estimation of Distribution Algorithms (EDA)
Swarm Intelligence:
Ant Colony Optimization
Bee Algorithm
Firefly Algorithm
Artificial Fish Swarm Algorithm (AFSA)
Bacterial Foraging Optimization (BFO)
Cuckoo Search Algorithm
Fuzzy Logic:
Fuzzy Control Systems
Fuzzy Inference Systems
Adaptive Neuro-Fuzzy Inference Systems
Type-2 Fuzzy Logic Systems

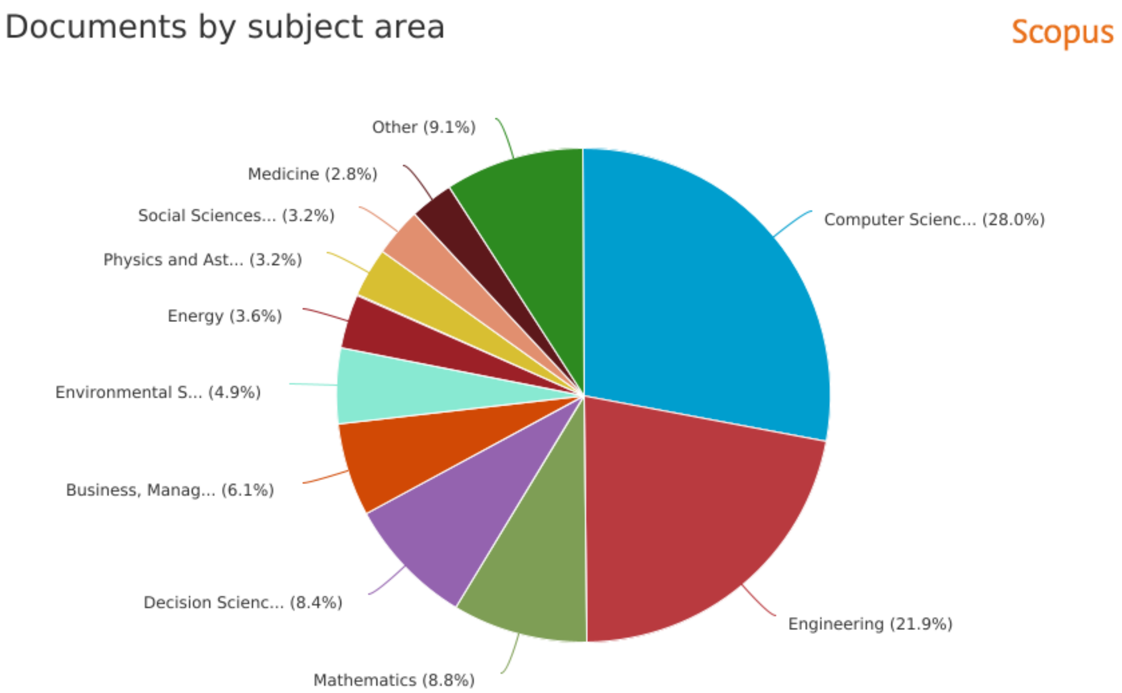
Fuzzy Clustering Algorithms (e.g., Fuzzy C-Means)
Fuzzy Multi-Criteria Decision Making
Bayesian Networks:
Hidden Markov Models
Dynamic Bayesian Networks
Gaussian Mixture Models
Kalman Filters
Naive Bayes Classifier
Markov Chain Monte Carlo (MCMC) methods
Explainable AI
Local Interpretable Model-agnostic Explanations
Shapley Additive Explanations
Counterfactual Explanations
Integrated Gradients
Feature Importance Measures (e.g., Permutation Importance)
Anchors
Cognitive Computing:
Expert Systems
Case-Based Reasoning
Rule-Based Systems
Intelligent Agents

4.4 LITERATURE REVIEW RESULTS

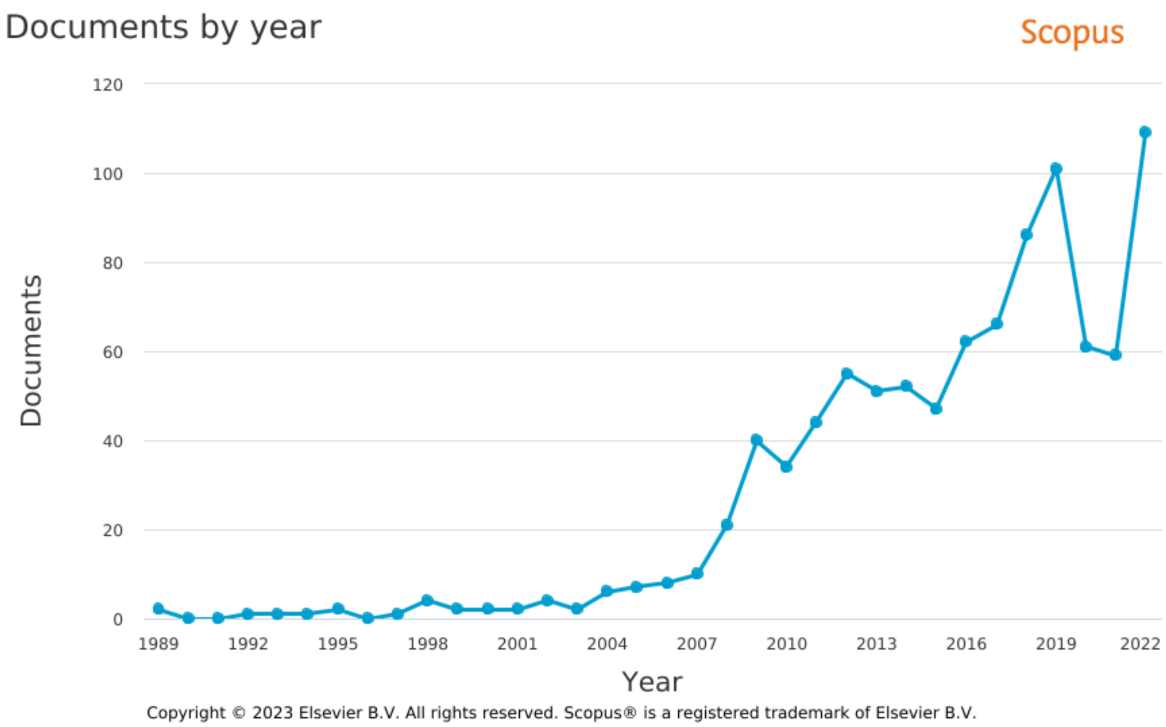
The key findings of our review showed 199 papers from 1989 to 2022 combining MCDA Methods with AI Technologies. A Scopus search (Stage 2) based on the query below produced 943 paper findings.

“TITLE-ABS-KEY ("AHP" OR "WSM" OR "TOPSIS" OR "PROMETHEE" OR "SAW" OR "GP" OR "DEA" OR "MOGA" OR "GRA" OR "VIKOR" OR "MACBETH" OR "F-TOPSIS" OR "SMAA" OR "BSC" OR "SODA" OR "SCA" OR "DEMATEL" OR "ANP" OR "RST" OR "UTASTAR" OR "UTA II" OR "UTADIS" OR "UTADIS I" OR "FUZZY UTA" OR "ELECTRE I" OR "ELECTRE II" OR "ELECTRE III" OR "ELECTRE TRI" OR "ELECTRE-TRI" AND "artificial intelligence" OR "Machine Learning" OR "Natural Language Processing" OR "NLP" OR "Knowledge Representation" OR "Cognitive Computing" OR "Reinforcement Learning" OR "Deep Learning" OR "Computer Vision" OR "Robotics" AND "DSS" OR "Decision Support System" OR "Decision Support Systems") AND PUBYEAR > 1988 AND PUBYEAR < 2023”

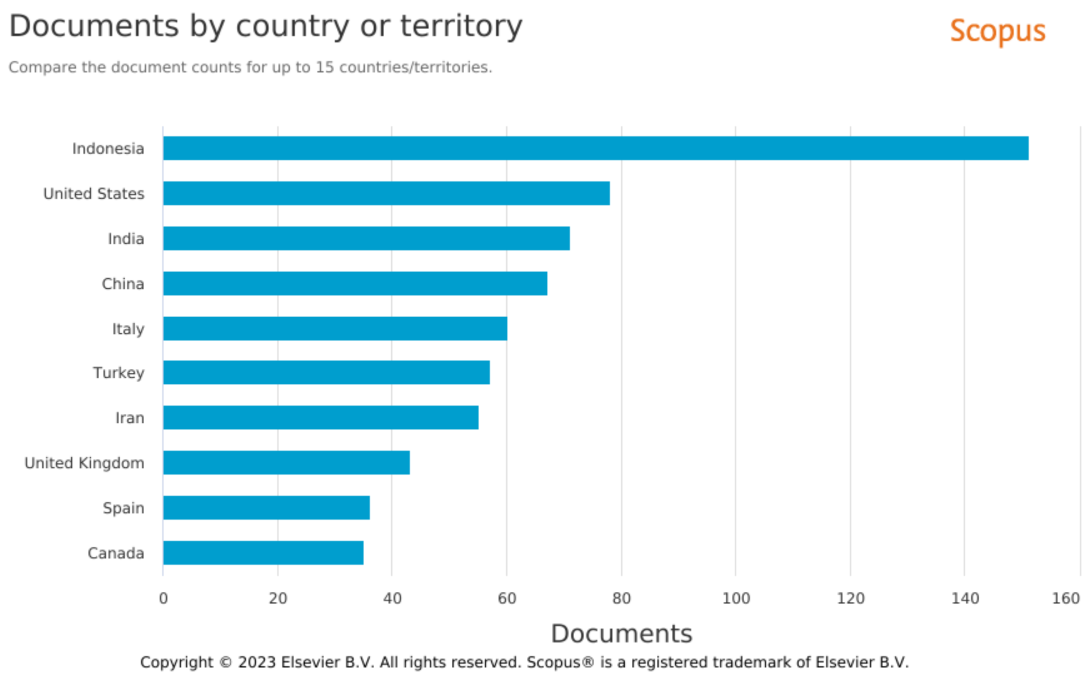

Stage 1:
DECISION SUPPORT SYSTEMS (DSS)
Stage 2:
DECISION SUPPORT SYSTEMS
(DSS) USING MCDA METHODS
943 results
Stage 3:
DECISION SUPPORT SYSTEMS
(DSS) USING BOTH MCDA
METHODS AND AI TECHNOLOGY
199 results



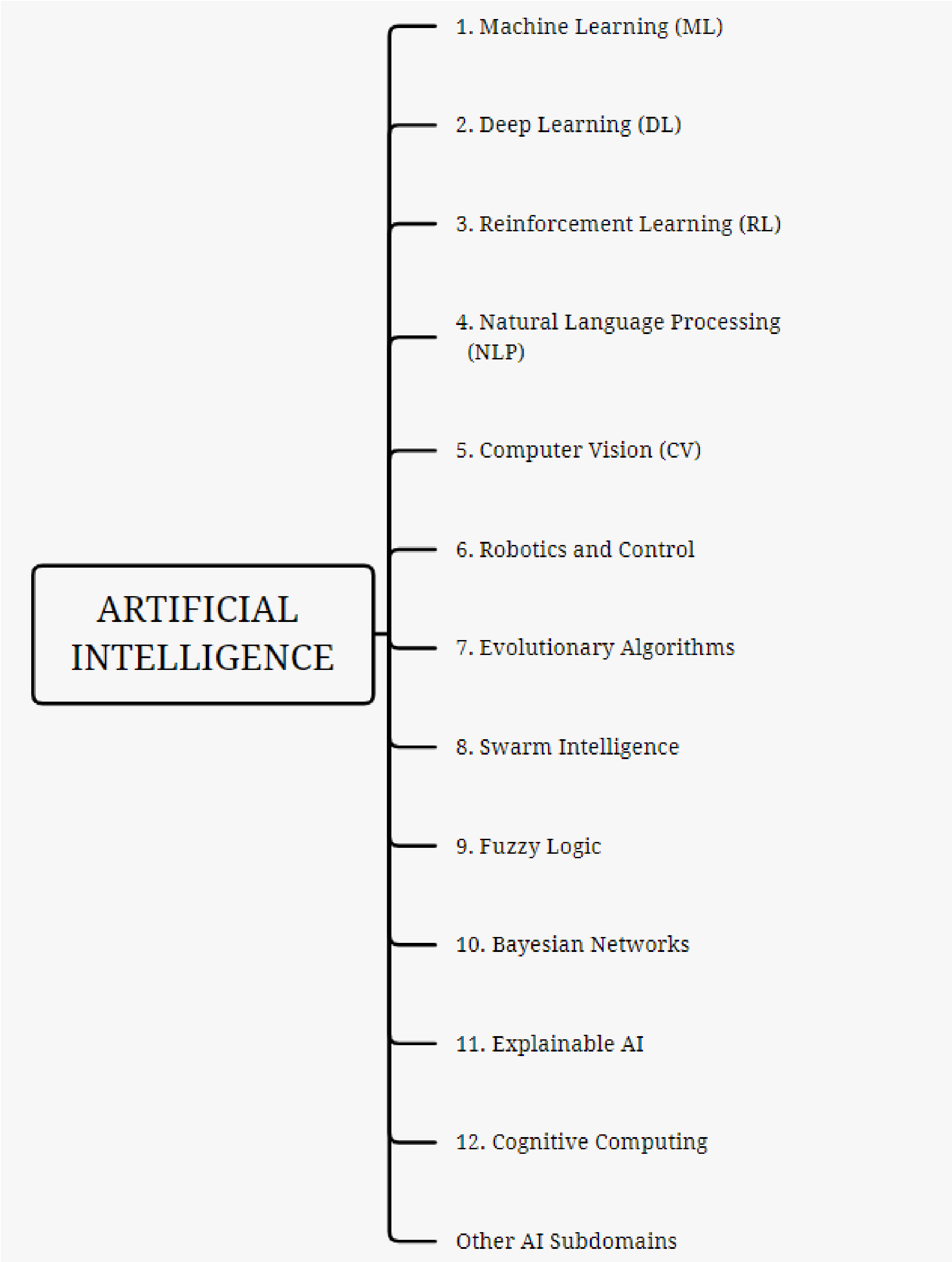
The three biggest subjects are our findings belong to are Computer Science, Engineering, Mathematics and Decision Science with percentages 28.0%, 21.90%, 8.8%, 8.4% respectively.



From 2008 until the end of 2022 the number of research papers combing AI and MCDA methods has quintupled. Top countries producing the underlying papers where Indonesia, United States, India, and China.



The Artificial Intelligence (AI) domains and methods were classified based on Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Natural Language Processing (NLP), Computer Vision (CV), Robotics and Control, Evolutionary Algorithms, Swarm Intelligence, Fuzzy Logic, Bayesian Networks, Explainable AI, Cognitive Computing. An

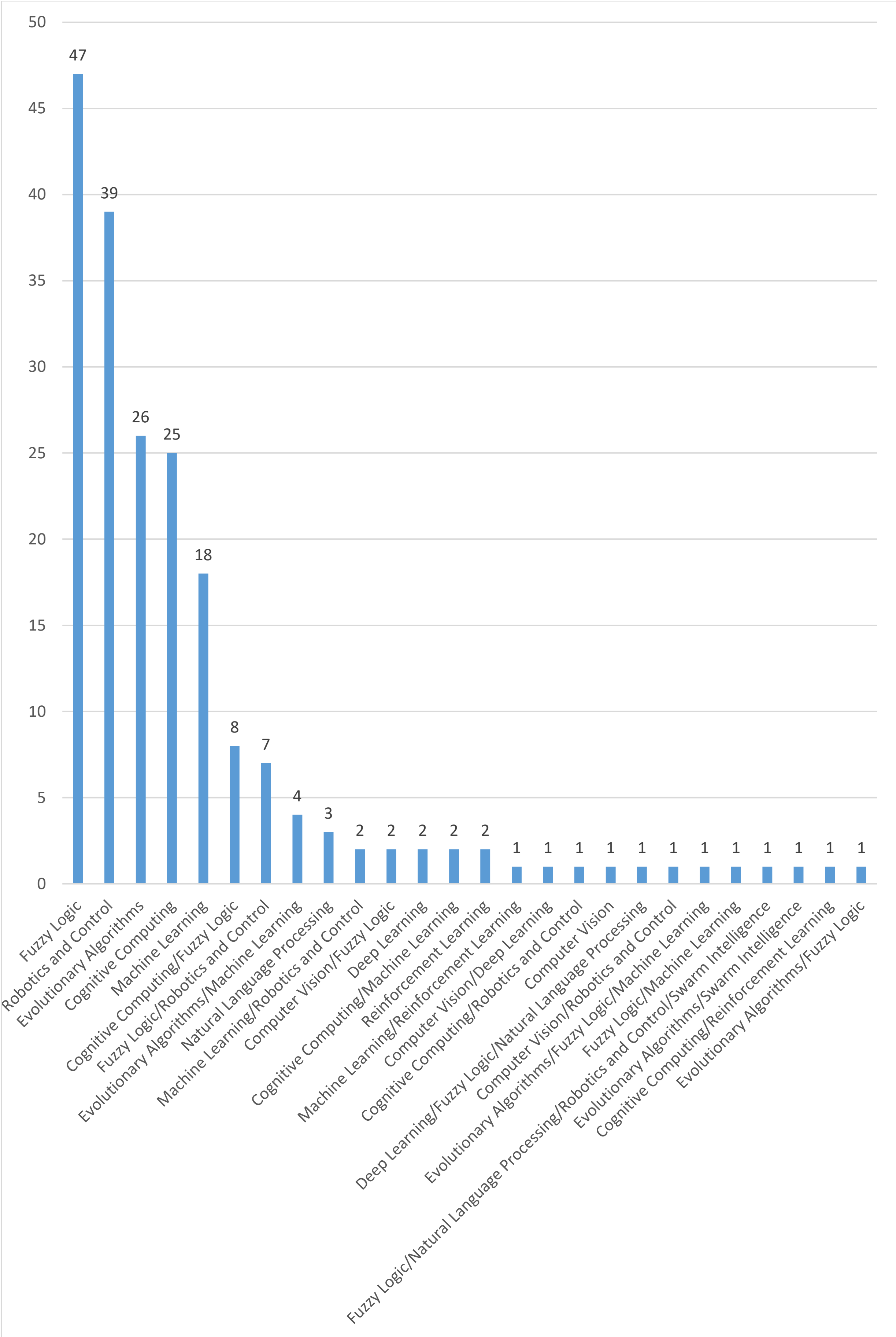


<u>Research Question 1: What are the key AI techniques used in MCDA methods, and what is their distribution in the literature?</u>

Many AI strategies with varied degrees of prevalence have been identified in MCDA methodologies through a literature review. Fuzzy Logic, Robotics and Control, Evolutionary Algorithms, Cognitive Computing, and Machine Learning are among the most important AI techniques. Fuzzy Logic accounts for 23.62 percent of all titles, followed by Robotics and Control (19.60 percent), Evolutionary Algorithms (13.07 percent), Cognitive Computing (12.56 percent), and Machine Learning (9.05 percent). Less prevalent are techniques such as Natural Language Processing, Computer Vision, Deep Learning, and Reinforcement Learning. The prevalence of AI techniques in published works demonstrates their usefulness and efficacy in addressing difficult decision-making issues. Fuzzy Logic, for example, is well-liked due to its capacity to deal with uncertainty and ambiguity in decision-making, which is a typical issue in real-world problems. Similarly, Evolutionary Algorithms and Machine Learning are also excellent for optimizing and learning from data, making them suited for MCDA tasks.

AI Methods	**Count of Titles**	**Count of Titles Percentage**
Fuzzy Logic	47	23.62%
Robotics and Control	39	19.60%
Evolutionary Algorithms	26	13.07%
Cognitive Computing	25	12.56%
Machine Learning	18	9.05%
Cognitive Computing/Fuzzy Logic	8	4.02%
Fuzzy Logic/Robotics and Control	7	3.52%
Evolutionary Algorithms/Machine Learning	4	2.01%
Natural Language Processing	3	1.51%
Machine Learning/Robotics and Control	2	1.01%
Computer Vision/Fuzzy Logic	2	1.01%
Deep Learning	2	1.01%
Cognitive Computing/Machine Learning	2	1.01%
Reinforcement Learning	2	1.01%
Machine Learning/Reinforcement Learning	1	0.50%
Computer Vision/Deep Learning	1	0.50%
Cognitive Computing/Robotics and Control	1	0.50%
Computer Vision	1	0.50%
Deep Learning/Fuzzy Logic/Natural Language Processing	1	0.50%

Computer Vision/Robotics and Control	1	0.50%
Evolutionary Algorithms/Fuzzy Logic/Machine Learning	1	0.50%
Fuzzy Logic/Machine Learning	1	0.50%
Fuzzy Logic/Natural Language Processing/Robotics and Control/Swarm Intelligence	1	0.50%
Evolutionary Algorithms/Swarm Intelligence	1	0.50%
Cognitive Computing/Reinforcement Learning	1	0.50%
Evolutionary Algorithms/Fuzzy Logic	1	0.50%
Grand Total	**199**	100.00%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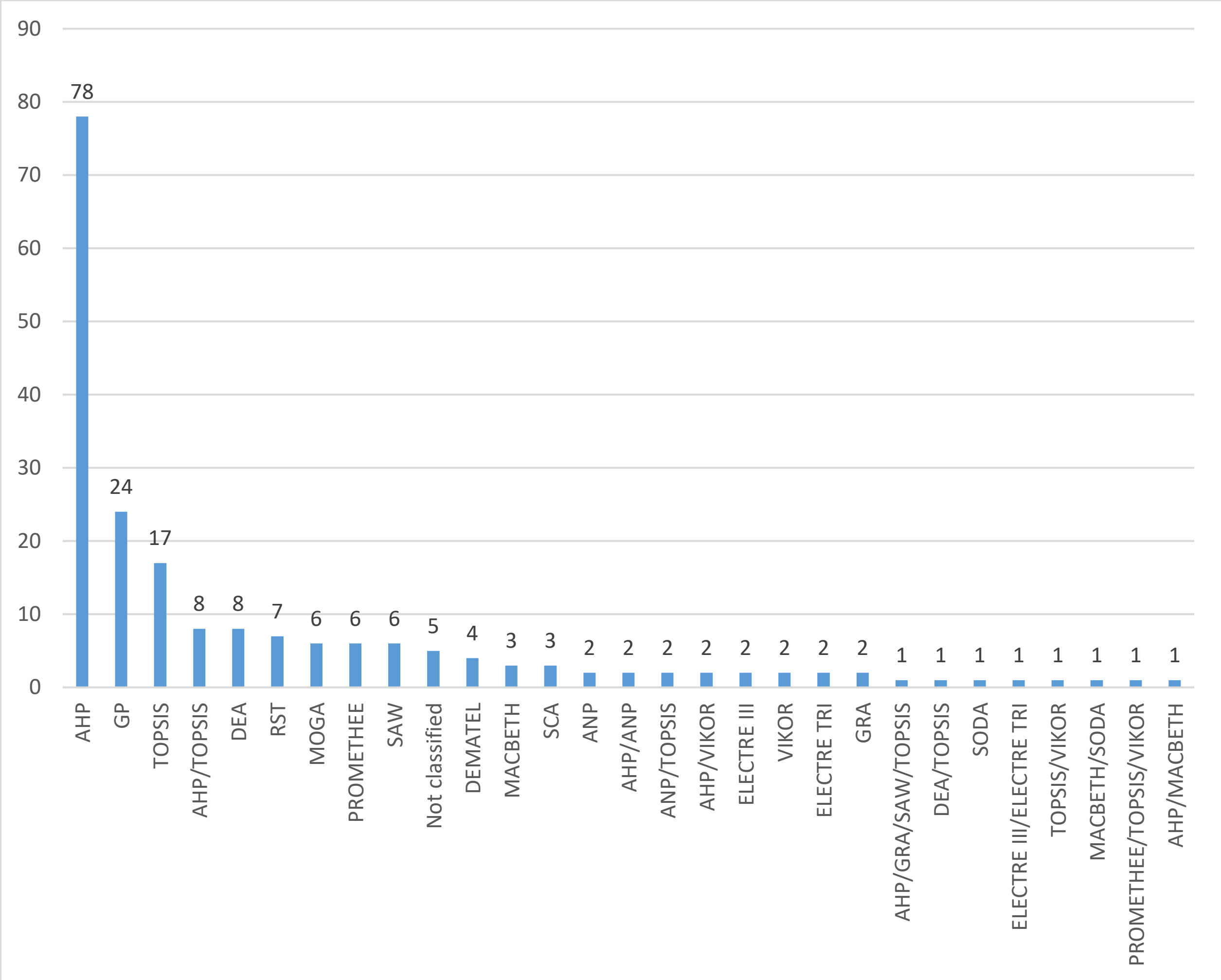
Fuzzy Logic
Robotics and Control
Evolutionary Algorithms
Cognitive Computing
Machine Learning
Cognitive Computing/Fuzzy Logic
Fuzzy Logic/Robotics and Control
Evolutionary Algorithms/Machine Learning
Natural Language Processing
Machine Learning/Robotics and Control
Computer Vision/Fuzzy Logic
Deep Learning
Cognitive Computing/Machine Learning
Reinforcement Learning
Machine Learning/Reinforcement Learning
Computer Vision/Deep Learning
Cognitive Computing/Robotics and Control
Computer Vision
Deep Learning/Fuzzy Logic/Natural Language Processing
Computer Vision/Robotics and Control
Evolutionary Algorithms/Fuzzy Logic/Machine Learning
Fuzzy Logic/Machine Learning
Fuzzy Logic/Natural Language Processing/Robotics and Control/Swarm Intelligence
Evolutionary Algorithms/Swarm Intelligence
Cognitive Computing/Reinforcement Learning
Evolutionary Algorithms/Fuzzy Logic

Research Question 2: How do AI techniques relate to MCDA methods, and are there any patterns or trends in the combination of AI techniques with specific MCDA methods?

The relationship between AI techniques and MCDA methods can be recognized when AI is used to improve the performance of particular MCDA procedures. The data provided shows the count of titles and the percentage distribution of various MCDA methods in the literature:

MCDA Methods	Count of Titles	Count of Titles Percentage
AHP	78	39.20%
GP	24	12.06%
TOPSIS	17	8.54%
AHP/TOPSIS	8	4.02%
DEA	8	4.02%
RST	7	3.52%
MOGA	6	3.02%
PROMETHEE	6	3.02%
SAW	6	3.02%
Not classified	5	2.51%
DEMATEL	4	2.01%
MACBETH	3	1.51%
SCA	3	1.51%
ANP	2	1.01%
AHP/ANP	2	1.01%
ANP/TOPSIS	2	1.01%
AHP/VIKOR	2	1.01%
ELECTRE III	2	1.01%
VIKOR	2	1.01%
ELECTRE TRI	2	1.01%
GRA	2	1.01%
AHP/GRA/SAW/TOPSIS	1	0.50%
DEA/TOPSIS	1	0.50%
SODA	1	0.50%
ELECTRE III/ELECTRE TRI	1	0.50%
TOPSIS/VIKOR	1	0.50%
MACBETH/SODA	1	0.50%

PROMETHEE/TOPSIS/VIKOR	1	0.50%
AHP/MACBETH	1	0.50%
Grand Total	**199**	100.00%



Due to the complementary nature of AI techniques and MCDA approaches, AI and MCDA techniques are frequently combined. AI techniques can solve some of the constraints or difficulties of MCDA methodologies, such as uncertainty management, solution optimization, and data-driven learning. These combinations illustrate the ongoing trend of incorporating AI approaches into decision-making processes in an effort to enhance their performance.

For example, the Analytic Hierarchy Process (AHP) is the most dominant MCDA method, appearing in 78 titles (39.20%). AHP is frequently combined with AI techniques such as Fuzzy Logic to address uncertainty and imprecision in decision-making. The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) appears in 17 titles (8.54%) and is also often paired with Fuzzy Logic for the same purpose.

Evolutionary Algorithms, such as Genetic Programming (GP) and Multi-Objective Genetic Algorithms (MOGA), are combined with MCDA techniques such as PROMETHEE, ELECTRE, and others to optimize solutions. GP is the second most prevalent MCDA method, appearing in 24 titles (12.06%), while MOGA appears in 6 titles (3.02%).

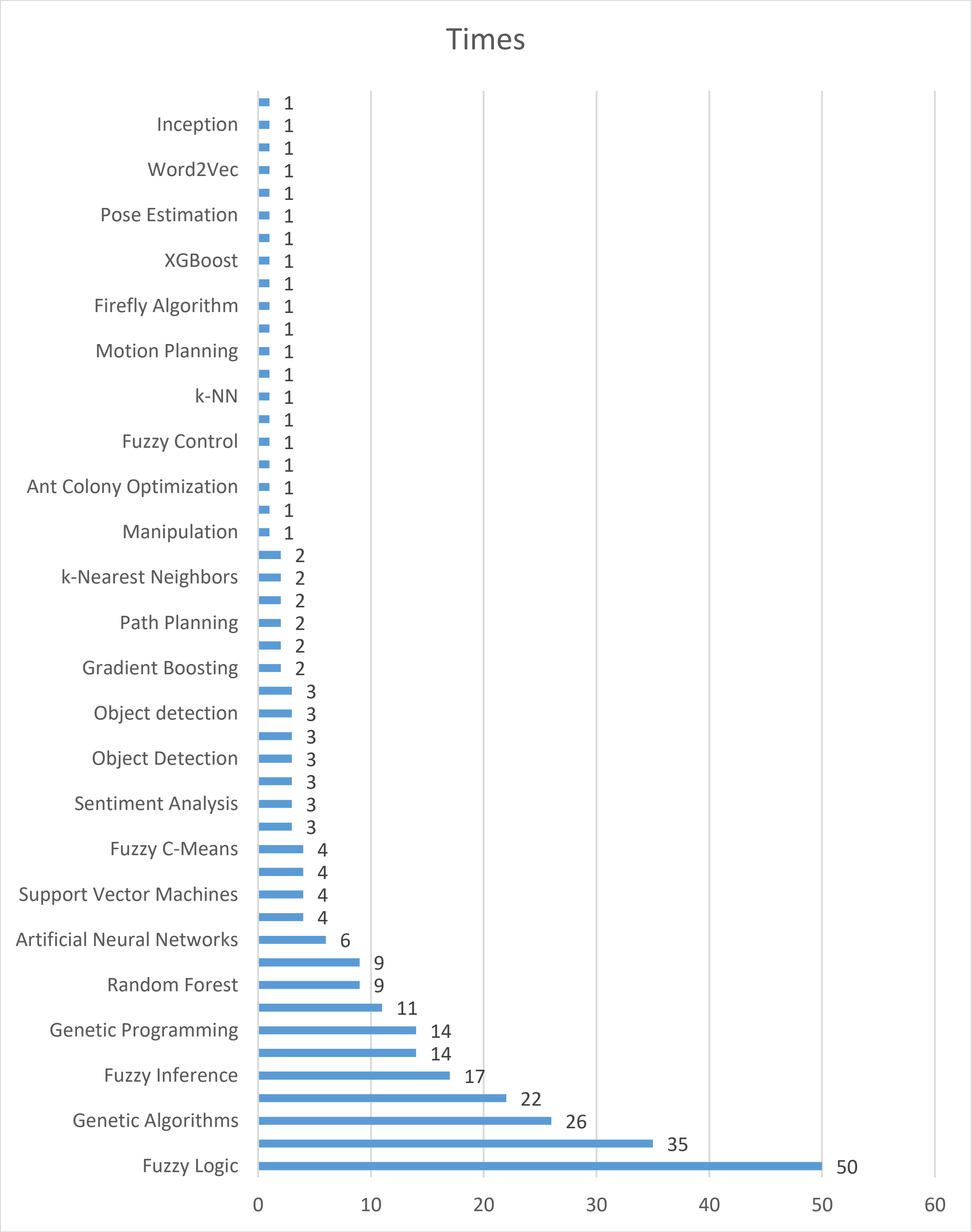
These trends and patterns in the combination of AI techniques with specific MCDA methods suggest that researchers and practitioners are actively exploring the synergistic potential of AI and MCDA approaches to enhance decision-making performance in various fields. By understanding these trends, researchers can identify potential opportunities for further integration of AI techniques with MCDA methods, ultimately contributing to more effective and informed decision-making processes.

AI	**MCDA**	**USES IN PAPERS**
Fuzzy Logic	AHP	20
Robotics and Control	AHP	19
Evolutionary Algorithms	GP	12
Cognitive Computing	AHP	10
Fuzzy Logic	TOPSIS	7
Evolutionary Algorithms	MOGA	6
Machine Learning	GP	6
Fuzzy Logic/Robotics and Control	AHP	5
Evolutionary Algorithms	AHP	5
Machine Learning	AHP	4

1. Fuzzy Logic - AHP: This combination appears 20 times in the dataset, making it the most dominant pairing. Fuzzy Logic helps in handling uncertainty and imprecision in decision-making, while AHP is a widely used MCDA method for structuring complex decisions.
2. Robotics and Control - AHP: Occurring 19 times, this combination suggests that AHP is frequently employed in robotics and control applications, potentially to handle decision-making processes in robot navigation, control systems, or task planning.
3. Evolutionary Algorithms - GP: This combination appears 12 times and indicates the usage of Genetic Programming, a type of Evolutionary Algorithm, to optimize the decision-making process in various problem domains.
4. Cognitive Computing - AHP: Found 10 times in the dataset, this combination suggests that AHP is a popular choice for structuring decision-making in cognitive computing applications, such as natural language processing, computer vision, or reasoning.
5. Fuzzy Logic - TOPSIS: This combination occurs 7 times and signifies the use of Fuzzy Logic to handle uncertainty in the TOPSIS method, another widely-used MCDA technique for ranking and selecting alternatives.
6. Evolutionary Algorithms - MOGA: With 6 occurrences, this pairing indicates the use of Multi-Objective Genetic Algorithms to optimize decision-making processes in various applications, particularly when multiple conflicting objectives need to be considered.
7. Machine Learning - GP: Also appearing 6 times, this combination shows the utilization of Genetic Programming in machine learning applications, such as feature selection, model optimization, or rule extraction.
8. Fuzzy Logic/Robotics and Control - AHP: Found 5 times, this combination suggests that Fuzzy Logic and Robotics and Control techniques are used

together with AHP to handle uncertainty and complex decision-making processes in robotics applications.

9. Evolutionary Algorithms - AHP: Occurring 5 times, this pairing implies that Evolutionary Algorithms, such as Genetic Algorithms or Particle Swarm Optimization, are used to optimize decision-making processes with the AHP method.
10. Machine Learning - AHP: Found 4 times, this combination indicates that AHP is used in machine learning applications for structuring decision-making processes, such as feature selection, model evaluation, or optimization.



Regarding the frequencies of AI keywords, Fuzzy Logic is the most common keyword (50 occurrences), followed by Mapping (35 occurrences) and Genetic Algorithms (26 occurrences). This suggests that Fuzzy Logic techniques are widely used in AI applications, particularly in combination with MCDA methods. Other frequent keywords include Expert Systems, Decision Trees, Genetic Programming, and Perception. It is important to note that some of these keywords may be related to the same AI technique or concept (e.g., Genetic Programming is a type of Evolutionary Algorithm).

Research Question 3: How do AI techniques contribute to the performance of MCDA methods, and what are the advantages and disadvantages of using AI techniques in MCDA?

In multiple ways, AI techniques improve the performance of MCDA procedures. First, they address the shortcomings of MCDA approaches, such as uncertainty management, solution optimization, and data-driven learning. Fuzzy Logic, for instance, can deal with imprecise and ambiguous data, making it suited for real-world decision-making challenges in which data may be incomplete or hazy. Evolutionary Algorithms are beneficial for optimizing solutions, particularly when numerous objectives and complex search areas are involved. Alternatively, Machine Learning approaches can learn from data and adapt to changing contexts, hence boosting the utility of MCDA methods in dynamic settings. The benefits of adopting AI approaches in MCDA include enhanced decision-making performance, applicability to a broader range of situations, and the capacity to adapt to changing circumstances. However, there are also downsides, such as the increasing complexity of the decision-making process, the need for greater processing resources, and potential problems with the outcomes' interpretability and transparency. Integration of AI techniques and MCDA methods may also necessitate a greater level of decision-maker skill due to the necessity to comprehend the underlying principles and assumptions of both AI techniques and MCDA methods.

Research Question 4: Based on the current state of AI techniques in MCDA, what are the potential future developments, and how can these advancements be applied to address real-world problems?

Future breakthroughs in the merging of AI techniques and MCDA methodologies may include the following:

- Improved AI techniques: As AI research advances, new techniques and refinements to old techniques may emerge, providing improved performance and application to a broader range of decision-making issues. For instance, developments in Deep Learning could result in more efficient feature extraction and representation in MCDA situations.

- Future research may concentrate on the development of hybrid AI-MCDA models that integrate several AI techniques with MCDA methodologies to address complicated, multifaceted decision-making challenges. These hybrid models might capitalize on the benefits of several AI techniques while compensating for their flaws, resulting in enhanced decision-making performance.

- Explanable AI (XAI) for MCDA: As the interpretability and transparency of AI techniques become more relevant, future research may concentrate on the development of explainable AI approaches for MCDA. These techniques would give decision-makers with a greater grasp of the reasoning behind the decision-making process, so fostering confidence in the results and allowing for more informed decision-making.

- Applications in the real world: Future advancements in AI techniques for MCDA could result in unique applications in domains such as healthcare, environmental management, transportation, and finance. These applications could aid in the resolution of complicated, real-world issues by offering more effective, data-driven support for decision-making.

Research Question 5: Considering the trends and patterns observed in AI techniques and MCDA methods, what recommendations can be made to

facilitate the effective integration of AI techniques with MCDA methods for improved decision-making?

On the basis of trends and patterns seen in AI approaches and MCDA methodologies, the following integration proposals can be made:

- Choose relevant AI techniques: Decision-makers should carefully analyze the characteristics of the decision-making problem and the specific requirements of the MCDA approach when selecting AI techniques. The MCDA method can be considerably enhanced by selecting the best appropriate AI technique.

- Integrate explainability and transparency: To facilitate trust and comprehension in the decision-making process, it is crucial to integrate explainable AI techniques with MCDA procedures. This will aid decision-makers in comprehending the reasoning behind the outcomes, allowing them to make more educated choices.

- Mixing several AI techniques with MCDA methods can assist in resolving complicated decision-making issues by harnessing the strengths of distinct AI techniques. To increase the efficacy and applicability of MCDA approaches, researchers and practitioners should consider building hybrid models.

- Collaboration across disciplines is necessary for the integration of AI techniques and MCDA approaches, which involves knowledge in both subjects. To enable the successful implementation of AI in MCDA, academics and practitioners should collaborate across disciplines and share their expertise and experiences to build creative solutions.

- Validate and evaluate performance: To guarantee the efficacy of AI techniques in MCDA, it is essential to validate and evaluate their performance using real-world data and benchmark challenges. This will aid in identifying potential flaws and improvement opportunities in the integration of AI techniques and MCDA approaches.

In conclusion, the integration of AI approaches with MCDA methodologies has substantial promise for enhancing the performance and applicability of decision-making. Researchers and practitioners can facilitate the effective integration of AI techniques with MCDA methods for improved decision-making support by selecting the most applicable AI techniques, incorporating explainability and transparency, developing hybrid models, collaborating across disciplines, and validating the performance.

Future developments are anticipated to result in even more effective AI-MCDA models and solutions, given the rapid evolution of AI technologies. By staying aware of these developments, decision-makers can utilize the most recent AI techniques to enhance their decision-making processes and tackle increasingly difficult problems in a variety of disciplines. This continual integration of AI and MCDA will continue to define the future of decision-making, giving vital recommendations for addressing real-world situations.

Moreover, as AI technologies mature and new methodologies emerge, the role of AI in MCDA will continue to evolve. It is essential for decision-makers and practitioners to remain abreast of these developments and be receptive to adopting and integrating new AI techniques into their decision-making processes. As AI becomes more prominent in MCDA, it will become increasingly vital for academics and practitioners to evaluate the ethical implications and potential biases associated with the use of AI in decision-making.

Chapter 5: CONCLUSIONS

The relationship between artificial intelligence (AI) and multi-criteria decision analysis (MCDA) is that AI approaches may be utilized to help the decision-making process in MCDA. MCDA is a method for systematically analyzing and comparing options using various criteria. It is frequently employed when there are numerous competing objectives and trade-offs must be made between them. For instance, in environmental decision-making, various stakeholders may prioritize economic development, environmental conservation, and social fairness differently. MCDA can assist in balancing these opposing goals and determining the optimal course of action based on all factors. AI may help the MCDA procedure in a variety of ways. For instance, AI algorithms may be used to evaluate and understand data associated with the decision-making process, such as evaluating the environmental consequences of various development projects. AI may also be used to find patterns and trends in the data that may not be immediately obvious to humans, which can aid in the identification of the most viable solutions. AI may also be used to automate portions of the MCDA procedure, such as determining the most significant criteria and creating alternate solutions. This can save the time and effort necessary to analyse and compare alternatives and guarantee that the process is consistent and objective. Consequently, the combination of AI with MCDA can increase the efficacy and efficiency of decision-making processes, especially in complex and dynamic contexts where several competing objectives must be balanced.

While AI models can give essential insights and decision-making help, they should not be depended on solely. In order to make educated and successful judgments, it is vital to combine AI models with human experience and knowledge. AI algorithms cannot duplicate the unique viewpoint that human experience and skill provide to decision-making. This involves recognizing the context and intricacies of a particular scenario, as well as the capacity to evaluate intangible issues like ethical and social considerations. Therefore, it is crucial that decision-making procedures use both AI models and human expertise in order to acquire the most thorough and well-rounded knowledge of the alternatives and their outcomes. This strategy will enable a more robust and productive decision-making process that incorporates both the objective facts and analysis supplied by AI models and the subjective insights and knowledge of people.

Through a comprehensive literature review, we have identified the key AI techniques employed in MCDA methodologies. Fuzzy Logic, Robotics and Control, Evolutionary Algorithms, Cognitive Computing, and Machine Learning are among the most prevalent AI techniques. The distribution of these techniques in the literature indicates their effectiveness and applicability in addressing complex decision-making problems. In particular, Fuzzy Logic is widely used due to its ability to handle uncertainty and ambiguity in decision-making, a common issue in real-world situations.

Our investigation reveals that AI techniques can be effectively integrated with MCDA methods to enhance their performance. For example, the Analytic Hierarchy Process (AHP), a widely used MCDA method, is frequently combined with Fuzzy Logic to address uncertainty and imprecision in decision-making. Similarly, the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) is often paired with Fuzzy Logic for the same purpose. The integration of AI techniques with specific MCDA methods indicates a trend towards leveraging the strengths of both methodologies for improved decision-making performance.

AI techniques have proven effective in enhancing the performance of MCDA methods by addressing their limitations, such as uncertainty management, solution optimization, and data-driven learning. For instance, Fuzzy Logic can handle imprecise and ambiguous data, making it suitable for real-world decision-making problems where data may be incomplete or vague. Evolutionary Algorithms are useful for optimizing solutions, particularly when multiple objectives and complex search spaces are involved. Machine Learning techniques can learn from data and adapt to changing contexts, thus enhancing the utility of MCDA methods in dynamic settings.

The ongoing development of AI techniques presents numerous opportunities for the future application of these methodologies in MCDA. As AI technologies advance, we can expect the emergence of new techniques and the refinement of existing ones, which will further enhance the performance of MCDA methods. Furthermore, the potential combination of multiple AI techniques in decision-making processes could lead to even more robust and accurate solutions, catering to a diverse range of complex problems across various domains.

In light of our findings, we offer several recommendations for integrating AI techniques with MCDA methods. First, decision-makers should carefully consider the appropriateness of specific AI techniques for their decision-making problem, taking into account the strengths and limitations of each methodology. Second, it is crucial to be aware of potential drawbacks associated with integrating AI techniques, such as increased complexity, the need for greater processing resources, and potential issues with interpretability and transparency. Finally, decision-makers should invest in the necessary skills and resources to effectively leverage the benefits of AI techniques and MCDA methods, ensuring a comprehensive understanding of the underlying principles and assumptions of both methodologies.

In conclusion, the integration of AI approaches and MCDA methodologies has the potential to considerably enhance the performance, applicability, and adaptability of decision-making across multiple disciplines. By adhering to the aforementioned recommendations and keeping abreast of the most recent developments in AI research, researchers and practitioners can ensure the effective application of AI in MCDA and contribute to more informed, data-driven decision-making across a broad spectrum of real-world problems.

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