Analysis of Intelligent Decision Support Systems and a Multi Criteria Framework for Assessment

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Abstract – The act of decision-making lies at the core of human existence and shapes our interactions with the surrounding environment. This article investigates the utilization of artificial intelligence (AI) techniques in the advancement of intelligent decision support systems (IDSS). It builds upon prior research conducted in the decision-making field and the subsequent development of decision support systems (DSS) based on that knowledge. The initial establishment of the fundamental principles of classical DSS is undertaken. The subsequent emphasis is directed towards the integration of artificial intelligence techniques within IDSS. The evaluation of an IDSS, as well as any other DSS, is a crucial undertaking in order to gain insights into the system's capabilities and identify areas that require enhancement. This article presents a review conducted on this significant yet insufficiently investigated subject matter. When utilized in conjunction with DSS, AI techniques such as intelligent agents, artificial neural networks (ANN), evolutionary computing, case-based reasoning, and fuzzy logic provide valuable assistance in defining complex practical challenges, which are mostly time-critical, encompass extensive and scattered data, and can derive advantages from sophisticated reasoning.

Keywords – Artificial Intelligence, Decision Support Systems, Intelligence Decision Support Systems, Evolutionary Computing.

I. INTRODUCTION

The capacity to engage in decision-making is a fundamental aspect of the human condition, as it enables us to exert influence over the surrounding environment. Sidhu and Pexman [1] engage in discourse regarding the optimal approach to facilitate individuals in making "sound" judgments, acknowledging the inherent capacity of humans to exhibit both commendable and unfavorable decision-making. The initial step in understanding how to facilitate decision-making is to categorize choices into organized, semi-structured, or unstructured classifications. Given the inherent clarity of optimal courses of action in structured choice scenarios, the provision of such assistance becomes superfluous. One illustrative instance of a problem that can be effectively tackled through analytical means, resulting in a precise solution, pertains to the determination of the most efficient route between two given locations. When faced with an unstructured dilemma, the decision maker is required to rely solely on their personal values and principles in order to make a choice. Selecting a life partner exemplifies a decision lacking a predetermined framework. Semi-structured issues can be characterized as falling within a spectrum that lies between two extremes. These issues necessitate human involvement or the consideration of individual preferences in order to arrive at a resolution, while still exhibiting certain shared characteristics. The decision of a business to enter international markets can be classified as a semi-structured decision.

Choice assistance is a suitable approach for addressing semi-structured choice problems due to its integration of user engagement and analytical methodologies, thereby enabling the generation of alternatives grounded in predetermined criteria and optimal outcomes. An intelligent decision-support system (IDSS) refers to a system that incorporates artificial intelligence (AI) techniques to generate potential solutions. It is emphasized by Rani and Garg [2] that detailed information on decision-making is imperative in order to maximize the potential of artificial intelligence. The field of artificial intelligence (AI) has made significant progress in its potential to support and augment the processes of decision-making, certainly in time-sensitive and complex situations. AI endeavors to replicate certain aspects of human decision-making.

The evolution of decision support systems (DSS) has been driven by the need to tackle a broader spectrum of challenges. Furthermore, the advent of web technologies has significantly influenced the various aspects of their design, development, implementation, and rollout. Despite the fact that the initial concept of a DSS was formulated prior to the widespread adoption of personal computers, its fundamental principle revolved around the utilization of interactive computing in the semi-structured decision-making context. The concept originated from the original proposal put forth by Michael Scot Morton for a Decision Management System. The initial conceptualization of DSS focused on computer-based interactive models, which enable decision-makers to employ models and data to handle unstructured challenges. However, Sprague argued in 1980 that this definition was overly restrictive, leading to an expansion of the term to encompass any model engaged in the process of decision-making. The proposed expanded definition of DSS may inadvertently result in the inclusion of all data systems utilized by managers or business professionals that do not fit into any other established category. Consequently, these systems may be overlooked or disregarded within the realm of DSS.

The DSS research area has witnessed divergent developments due to various schools of thought and a multitude of decision-support-related factors. Over time, the diverse nature of decision-making support systems has led to a lack of clarity in understanding their theoretical foundations, evaluation techniques, design and development techniques, support mechanisms, architectural forms, including organizational and managerial aspects. Wu, Chen, and Gao [3] have extensively examined and analyzed the various advantages offered by Decision Support Systems (DSS) from multiple perspectives]. The evolution of decision support systems (DSS) can be traced through four generations. The first generation introduced data-centric DSS, which was followed by the second generation that featured DSS with enhanced user interfaces. The third generation of DSS placed a greater emphasis on models, while the fourth generation witnessed the emergence of web-based DSS.

This article will examine the topic of study indecision making, explore decision support systems (DSS) constructed based on this knowledge, and investigate the utilization of artificial intelligence (AI) methodologies to enhance the effectiveness of IDSS. The rest of the sections will be arranged as follows: Section II presents a background analysis of the human decision-making process. Section III introduces the concept of decision support systems. Section IV focusses on intelligent decision support systems. In Section V, a discussion of a multi-criteria framework for IDSS assessment is provided. Lastly, Section VI draws final remarks to the article.

II. BASICS OF HUMAN DECISION MAKING

In recent times, our focus has been directed towards the development of a theoretical framework that encompasses the cognitive processes involved in human decision-making. Specifically, our research aims to elucidate the intricate dynamics that arise when individuals are confronted with the task of selecting among multiple alternatives, while concurrently considering the contextual nuances that surround these choices. Exemplary instances of such tasks include the AX-CPT (Continuous Performance Test) and the Flanker-Erickson task, which are frequently employed within the domain of cognitive neuroscience. In the latter scenario, the primary stimulus (X/Y) is introduced alongside a contextual stimulus (A/B) that may be similar or contrasting. The subject's decision is solely influenced by the primary stimulus, disregarding the contextual stimulus.

Conversely, in the former scenario, the subject is initially presented with the context-principal pair, followed by the primary stimulus (X/Y). The subject's response is contingent upon the context-principal pair. In the fourth study, a Bayesian update was employed to develop the Contextual Drift-Diffusion Model (CDDM), taking into account its inherent limitations. This model offers a comprehensive account of empirical findings related to decision-making in context, thereby providing a satisfactory explanation. Algorithms were developed in [4] to estimate parameters for human decision-making data in the context of cognitive and computational models. In the sixth reference, the relationship between the Contextual Dynamic Decision Making (CDDM) and optimal decision-making was examined by investigating contextual decision-making challenges within the framework of a Markov decision process.

Lee and Liu [5] provide a comprehensive overview of research pertaining to human decision making. The authors contend that reasoning and recognition, which are considered the fundamental components of effective decision-making, are intricately interconnected. The ability to engage in reasoning, which involves the assessment of various alternatives and the sorting of the best option based on individual requirements, is regarded as a distinguishing characteristic of sound judgments in human beings. Integrative Data Science Systems (IDSS) encompass a diverse range of reasoning approaches, as they can be effectively articulated through analytical methodologies. Naturally, not all choices necessitate the application of logic. Conversely, an acquired response predicated upon the identification of stimuli may lead to an action or decision lacking any apparent justification.

Significant progress has been made in understanding the process of formulating responses or reaching conclusions in time-constrained situations. In a notable study, Bond and Cooper [6] examined the phenomenon of "recognition-primed decisions" through an investigation into the decision-making strategies employed by firefighters and other individuals in emergency response roles. Klein argues that pattern-matching is particularly advantageous in situations where the application of human expertise or prompt decision-making is essential for achieving a favorable outcome. When utilizing decision assistance, it is imperative that the system exclusively offers pertinent information and places a greater emphasis on cognitive load for the human user. The prefrontal lobe of the brain, commonly acknowledged as the anatomical site associated with cognitive processes, is widely recognized as the neural substrate underlying the capacity for decision-making.

The occurrence of damage to this particular cerebral region results in irrational decision-making and an altered sense of peril. Halder, Associate Professor - St. Xavier's University, Kolkata., Samajdar, and Assistant Professor - Brainware University, Kolkata [7] have demonstrated that emotional states within the brain exert discernible influences, both overt and covert, on the decision making process. The investigation of effectively incorporating emotion into machine reasoning is a topic that warrants further scholarly examination. Nevertheless, recent study in the domain of IDSS has demonstrated promising prospects in the incorporation of affective characteristics, such as emotion, into the decision-making process. According to Brick, McCully, Updegraff, Ehret, Areguin, and Sherman [8], the process of decision making is dependent on the utilization of working memory. IDSS possess the capability to emulate the decision-making processes by leveraging computer technologies such as symbolic reasoning, memory, and the acquisition and interpretation of data. Various systems for DSS and IDSS have been introduced, all of which rely on models that simulate human decision-making processes. Fetanat, Tayebi, and Moteraghi [9] introduced a decision-making framework that has subsequently been referred to by various names, including the Subjective Expected Utility Model, the Expected Utility Model, and the Expected Utility Model.

Based on Schoemaker and Russo's [10] assumption, it is posited that an individual tasked with making decisions can achieve the highest level of expected utility by considering a given collection of states, a collection of potential results, and suitable functional order from states to results that adhere to specific postulates, including transitivity. If one possesses knowledge of the probability associated with a sequence of events, Rincón and Santana's [11] theorem can be employed to ascertain the optimal course of action that is expected to yield the greatest benefit. Sudret, Podofillini, and Zio [12] introduced a theoretical framework for decision-making under conditions of uncertainty. Several critiques have been directed towards Savage's theory as a result of the assumptions that the makers of decisions possess the ability to assess all the implications of actions [13]. This assumption necessitates cognition of future occurrences along with their corresponding prospects. Among the Savage's significant accomplishments was his ability to analyze and distinguish between causes, effects, and agency.

Wakker [14] recognized Savage's theoretical limitation and presented the bounded rationality theorem. Rationality refers to the cognitive process by which decision-makers are bound by limitations imposed by their level of knowledge, temporal constraints, and cognitive abilities. The seminal research conducted by Herbert A. Simon in 1955 introduced a behavioral perspective on decision making, establishing a model for normative process integrating three initial stages, which were later expanded to include a fourth stage. These stages are as follows: i) intelligence; ii) design; iii) choice; and iv) implementation. During the Intelligence stage the decision maker acquires knowledge about the matter under consideration, develops the necessary course of action, and gathers relevant data related to the decision problem. The identification of pertinent variables, establishment of decision criteria, specification of relationships between variables, development and utilization of a decision model, and exploration of potential decisions are all integral components of the Design phase. During the Choice stage, the decision makers assess the available options and chooses the option that most effectively meets the decision criteria. During the final phase of Implementation, commonly referred to as Review, the decision maker engages in a thoughtful analysis of the potential consequences of the chosen course of action. This entails formulating a comprehensive implementation strategy, procuring the necessary resources, and subsequently executing the devised plan.

Feedback loops are available between the different stages, enabling the decision maker to revisit a previous step or initiate a new process of decision-making oriented on the results of the implementation phase. The OODA Loop delineates the sequential activities of Observe, Orient, Decide, and Act. This model, which remains unpublished, bears resemblance to Simon's model and is frequently employed by military researchers to facilitate decision-making processes. Saunders and Souva's [15] methodology was predicated on empirical evidence indicating that American pilots achieved a higher rate of success in aerial combat despite being at a disadvantage in terms of firepower during World War II. This advantage stemmed from the pilot's increased likelihood of early enemy detection in the initial phase of observation, affording them additional time to effectively assess and respond to the imminent threat.

The pilots of the United States Air Force exhibited a higher level of decisiveness compared to their adversaries due to their superior equipment and ability to effectively utilize their training in order to assess the available information and execute appropriate actions. Boyd's arguments on "patterns of conflict" and "a discourse on winning and losing" have had a significant influence on military strategy and decision-making. DSS were established in respect to Albahri et al.'s [16] theory of limited rationality and the recognition of decision making process considered as a critical process. Simon's concept of limited rationality was found to be an appropriate framework for understanding and describing the decision making processes employed in management. According to Turpin and Marais' [17] model, the decision maker is not obligated to possess complete information, and the ultimate goal of the model is to achieve a state of satisfaction by making judgments that may be suboptimal.

Shaddy, Fishbach, and Simonson [18] referred to the trade-offs as "satisficing" rather than "maximizing". In contrast to the maximization approach, wherein agents allocate preferences or value to every conceivable outcome of each alternative actions and choose the mostly utilized one, the satisficing approach acknowledges that it is rational to pursue any action that results in an acceptable outcome. According to Simon, there exist multiple factors that influence decision-making, some of which may be in conflict with each other. Humans often exhibit a tendency to eschew decision-making processes that necessitate the consideration of multiple factors. This inclination stems from their reliance on heuristics, shortcuts, localized adaptations, aversion to potential losses, and a propensity to mitigate risks. Decisions made using sub-optimal procedures are susceptible to cognitive biases, which encompass various common errors such as anchoring, status quo bias, confirmation bias, framing effects, estimation and forecasting biases, and the sunk cost fallacy. The concept of "anchoring" pertains to the phenomenon wherein individuals assign excessive significance to the initial piece of information they encounter, subsequently influencing their evaluations and judgments in future comparative contexts. The term "status quo" refers to the endeavors aimed at maintaining the existing state of affairs.

The concept of "confirming evidence" refers to the act of actively seeking information that supports a particular judgment or belief, while consciously avoiding or disregarding evidence that may contradict it. One instance illustrating the framing phenomenon involves the presentation of a decision in a manner that emphasizes the potential benefits and drawbacks associated with each alternative. When individuals are faced with decision-making situations, they frequently exhibit a tendency to overestimate their capacities to evaluate and predict outcomes, a phenomenon that becomes particularly pronounced when confronted with unfamiliar events. Finally, the concept of sunk cost emerges when decision-makers opt to justify prior actions despite evidence indicating that such justifications will hinder future progress. IDSS play a critical role in assisting individuals in mitigating their cognitive limitations and biases by offering a rational framework for evaluating and comparing various options. Prior to delving into the integration of artificial intelligence (AI) methodologies into IDSS, it is essential to establish a solid understanding of the foundational principles of traditional DSS.

III. DECISION SUPPORT SYSTEMS

Decision support systems (DSS) encompass various interactive computer systems, which enable decision makers to utilize knowledge, models, and data tackle situations that are unstructured, ill-structured, and semi-structured. DSS facilitate the active involvement of decision makers in the decision-making process by allowing them to provide input, conduct queries, explore for further explanations, review output, and engage in other relevant activities. There is a wide range of diverse DSS available, each designed to cater to specific user groups and address distinct problem domains. This is primarily because the majority of DSS are developed with the intention of resolving a singular problem or a limited number of interconnected issues. DSS have the potential to assist in a wide range of activities, including management and creative problem-solving. These systems can be designed to cater to the needs of either one or multiple decision makers.

Various categories of DSS have been assigned distinct labels in order to align with their target users. These classifications include Group DSS, Expert Systems, Collaborative DSS, Clinical DSS, Adaptive DSS, Intelligent DSS, Executive Support Systems, and others. According to Liu, Fei, and Mi's [19] model of decision-making, single-user decision support systems (DSS) generally consist of three main modules: Processing (Design), Output (Choice), and Input (Intelligence), Given that theories regarding human cooperative decision making are still in the early stages of development, it follows that group or collaborative decision support systems (DSS) are currently undergoing research and development. Similar to the existence of theories regarding the creative process, there is currently an emergence of Decision Support Systems (DSS) aimed at facilitating creativity and the generation of ideas.

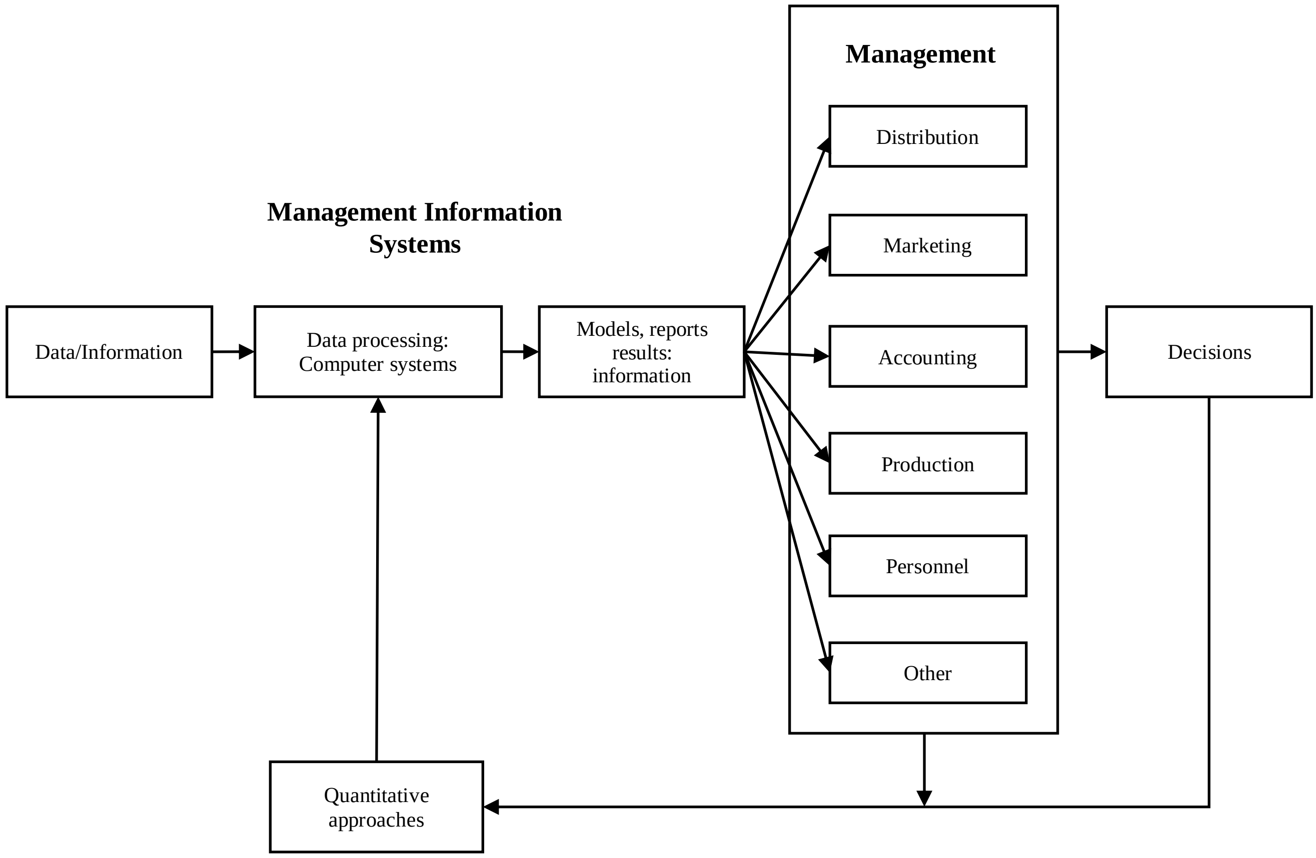

Fig 1. The DSS Structure

Decision support systems (DSSs), as depicted in **Fig 1**, are specifically developed to tackle emerging and ever-changing problems that lack a pre-established solution methodology. A proficient structured DSS facilitates decision-makers in consolidating information from diverse sources, encompassing raw data, documentation, and the firsthand expertise of workers, managers, and executives. DSS are commonly juxtaposed with Decision Management Systems (DMS), which offer a heightened level of automation the process of decision-making. The utilization of DSS has garnered significant recognition within the academic community due to its ability to enhance and streamline the process of decision-making. The utilization of DSS is perceived by its users as a mechanism to enhance the efficiency and effectiveness of internal organizational processes. Certain authors have expanded the conceptual boundaries of DSS to encompass any system that has the potential to facilitate the decision-making process.

IV. INTELLIGENT DECISION SUPPORT SYSTEMS

The IDSS based on AI offer valuable data and guidance to aid individuals in making optimal decisions. IDSS utilize a diverse array of data sources, amalgamate and scrutinize the information, and subsequently furnish the findings to analysts. Subsequently, the AI decision-making systems offer guidance and effectively communicate it to users in a comprehensible manner. Presently, the primary challenge faced by numerous organizations and investors lies not in the acquisition of sufficient data, but rather in the intricate process of analyzing said data and subsequently implementing the derived insights. This is precisely why the utilization of decision-making aids that can harness the computational capabilities of artificial intelligence is advantageous. AI decision support systems enable organizations and investors to expedite and enhance their decision-making processes by automating data processing and analysis, thereby generating data-driven recommendations.

According to a particular definition of intelligence, it is asserted that intelligence is primarily focused on rational action. This implies that an intelligent machine would consistently make optimal decisions given the prevailing circumstances. In order to accomplish this objective, an IDSS is a type of DSS that exhibits attributes associated with "intelligent behavior". These attributes include the ability to learn from past experiences, comprehend ambiguity and contradiction, react effectively and promptly to unfamiliar circumstances, utilize knowledge to modify or comprehend the ecosystem, and distinguish the relative importance of different factors. The Institute for Data, Systems, and Society (IDSS) employs a diverse array of artificial intelligence (AI) techniques. These methods are being increasingly applied in various practical and consequential domains. The enhancement of human decision making can be observed across various contexts, ranging from healthcare assistance to corporate decision making. In the subsequent sections, we will explore the fundamental principles underlying the most prominent artificial intelligence methodologies and their significance in the decision making process.

ANNs for Intelligent Decision Support

To address a given issue, a network, referred to as neural network (NN) or artificial neural network (ANN). comprises numerous interconnected subnetworks, commonly known as neurons. Neural networks (NN), akin to the layered structure of neurons in the brain, draw inspiration from the brain's architecture for information processing. One notable advantage of neural networks is their ability to effectively approximate bounded continuous functions while maintaining a negligible level of approximation error. In general, a neural network (NN) undergoes training through iterative exposure to a dataset containing predetermined outputs. This process enables the NN to acquire a set of weights that enhance its capacity to generate outputs that closely approximate the predetermined ones. The neural network (NN) can be utilized for making future predictions based on the given inputs. Additionally, it has the capability to adapt and improve its performance by adjusting its weights in accordance with new input/output data. The capacity of neural networks (NN) to identify patterns, extrapolate to novel scenarios, and classify data through observation mirrors the cognitive process employed by individuals to draw inferences about future occurrences by analyzing evidence from previous experiences or present conduct.

Neural networks (NN) exhibit a clear differentiation from logic-based, sequential techniques, which consider a form of connection between output and input elements. The main merit of neural networks is their ability to naturally incorporate nonlinearity when adjusting the weights. Neural networks (NN) offer decision support in scenarios where logic-based methods, such as fraud detection, face challenges in accurately describing the situation. Nevertheless, neural networks are not deemed suitable for tasks involving data processing. There exist three distinct methods through which neural networks can acquire knowledge of the underlying function within a dataset. These methods, namely unsupervised learning, supervised learning, and reinforcement learning, all necessitate the utilization of training data. Unsupervised learning refers to the type of learning in which the neural network is solely presented with inputs and is deficient of the corresponding outputs. The major objective is to uncover latent patterns within the dataset. Supervised learning enables the neural network to acquire the ability to approximate desired outputs with a certain level of precision by presenting it with sample inputs and their corresponding outputs (targets).

The neural network can be utilized for making predictions using a new set of inputs once the weights associated with the inputs have been determined. In numerous practical situations, it is common for input-output n-tuples to be unattainable, resulting in a non-existent or limited amount of outputs following a substantial amount of inputs. In order to address this issue, the utilization of reinforcement learning is employed to provide feedback to the neural network regarding the suitability of the weights it has chosen. In order to facilitate the applicability of the neural network for generalization and prediction purposes, it is imperative to train it in a manner that avoids over-fitting, which refers to excessive conformity to the training data. The term "black boxes" is commonly employed to refer to neural networks, indicating that comprehending the inner workings of the model may pose a challenge for the decision maker. The decision rules and interactions among variables within a neural network are not readily observable due to the distributed nature of computation across multiple nodes and hidden layers.

Fuzzy Logic for Intelligent Decision Support

Fuzzy logic offers enhanced decision support by incorporating variable or input representation in the process of decision-making that aligns with human cognitive processes. Decision makers often encounter challenges related to imprecise or ambiguous inputs. Weather conditions can encompass various states, such as clear, partially cloudy, overcast, or cloudy. In contrast, Boolean logic refers to a symbolic model of logic, which controls logical activities on computers and is grounded in a binary system consisting of two values: 0, representing complete falsehood, and 1, representing absolute truth. Fuzzy logic allows for the uncertainty representation by permitting inputs to vary between the values of 0 (indicating complete falsehood) and 1. According to Wang, Xu, and Gou [20], fuzzy logic possesses the capacity to be advantageous in the context of IDSS due to several reasons. Firstly, it provides flexibility by accommodating unexpected circumstances. Secondly, it offers intuitive options such as "likely" or "very good" to aid decision-making. Thirdly, it enables the exploration of hypothetical scenarios. Fourthly, it minimizes the risk of making incorrect choices by providing multiple values to select from. Lastly, it provides modeling techniques that are suitable for addressing uncertainty issues, which are challenging to represent using traditional computational models.

Fuzzy logic provides users with increased flexibility in data representation, thereby expanding their decision-making options and allowing for greater latitude in estimating input values. Due to its lack of predetermined structure, fuzzy logic enables the organic and effortless capture of nonlinear interactions. The decision-maker possesses an inherent mechanism to address uncertainty through the utilization of values that can be easily refined and adjusted in response to the acquisition of new information. Fuzzy logic enables the representation of rule-oriented behaviors like expert knowledge, in a manner that facilitates their collection and provision to decision makers at the required timeframe. The clarification of the significance of decision variables can be achieved through the combination of neural networks and fuzzy logic. Input variables can be defined by specifying their maximum, minimum, and expected values.

The provided explanations in the native language of the decision makers serve the purpose of enhancing the model's comprehension of the domain expertise of the decision maker. The incorporation of human-comprehensible interpretation into the multilayer feedforward neural network can be achieved through the utilization of fuzzy logic NN, which are a type of decision model. Referential neurons play a role in facilitating predicate-based processing, which involves operations such as greater than, less than, or comparability, as stated in the fuzzy logic framework. On the other hand, aggregative neurons are responsible for executing AN-OR logic. The utilization of fuzzy-logic neural networks enhances the process of decision-making by addressing certain limitations of traditional neural networks, particularly in terms of transparency.

Fuzzy logic provides a comprehensive and intricate approach to the analysis of knowledge, which is of paramount importance in making well-informed decisions when confronted with situations characterized by uncertainty and ambiguity. The integration of fuzzy logic with conventional decision-making approaches yields significant enhancements in both accuracy and adaptability. A fuzzy logic system typically consists of four components: The system consists of three main components: the defuzzification interface, the inference engine, and the fuzzy rule base. Initially, it is necessary to employ fuzzification techniques in order to convert the linguistic inputs utilized as source data into fuzzy integers. The fuzzy rule base comprises a collection of distinct fuzzy IF-THEN rules that can be employed in various specific scenarios. Fuzzy logic systems depend on an inference engine to execute the process of reasoning in accordance with the principles of fuzzy logic. Finally, the defuzzification interface is responsible for converting the fuzzy results obtained from the inference process into linguistic outputs.

Expert Systems for Intelligent Decision Support

The concepts of "Decision Support System" (DSS) and "Expert System" (ES) have gained significant traction within the realm of information technology in recent times. The current state of the art in both disciplines, namely Expert Systems (ES) and DSS, demonstrates significant variations along these dimensions. The ES method can be considered as an indispensable supplement to conventional quantitative modeling approaches. The development of "programmable" judgments represents a significant advancement; however, domains in which constructing an expert system is even remotely feasible must satisfy numerous rigorous criteria. Hence, the programming of an Expert System (ES) to undertake all managerial decisions is deemed unattainable.

The Expert System (ES) refers to a computer program that has been specifically developed to carry out tasks that are typically executed by a human expert. Systems that incorporate the expertise of one or more identifiable individuals are occasionally denoted as "expert systems" (ES). The initial step for the system developer involves acquiring an understanding of the cognitive processes employed by the human expert in order to reach a conclusion. Subsequently, this acquired knowledge is integrated into the program. One category of knowledge-based systems is referred to as IEDSSs, which stands for IDSS. The consolidation of expertise from multiple sources can be achieved through the utilization of a method that allows for the compilation of information into a single, user-friendly database.

Computational neuroscience, cognitive science, artificial intelligence, philosophy, knowledge engineering, and computer science represent a subset of the disciplines upon which Intelligent Educational Decision Support Systems (IEDSSs) are constructed. In this manner, Intelligent Electronic Decision Support Systems (IEDSSs) exhibit resemblances to the cognitive processes of the human mind. Knowledge-based systems are characterized by their non-algorithmic nature and their ability to engage in inference, reasoning, perception, learning, and other cognitive processes. The Intelligent Entity Decision Support System (IEDSS) has the capability to incorporate human-provided information and utilize simulated cognitive processes to generate problem-solving strategies. Air navigation, geology, biology, economics, medicine, healthcare, business, and education represent a limited selection of the numerous disciplines that could potentially derive advantages from the utilization of Intelligent Environmental Decision Support Systems (IEDSSs) in contemporary times.

Evolutionary Computing for Intelligent Decision Support

Evolutionary computation is a subfield within the realm of artificial intelligence and soft computing, which focuses on the examination and development of a collection of algorithms designed for the purpose of achieving global optimization. These algorithms draw inspiration from the principles underlying the process of natural selection. More precisely, these solvers can be classified as belonging to the category of metaheuristic or stochastic optimization algorithms, which employ a trial-and-error methodology using a significant number of samples. Evolutionary computing involves the initial formation of a pool comprising potential solutions, which subsequently undergoes iterative refinement over time. Each successive generation is formed through the random elimination of less preferred options and minimal modification of the remaining ones.

In the field of biology, natural selection and artificial selection are two fundamental processes employed to enhance the quality of a population of solutions. These processes play a crucial role in shaping the evolutionary trajectory and genetic makeup of organisms. Consequently, the population will gradually evolve in order to enhance its fitness, as evaluated by the predetermined fitness function of the algorithm. Evolutionary computing methods are extensively employed within the realm of computer science due to their capacity to offer highly efficient solutions across a diverse range of problem contexts. There exists a wide array of versions and extensions, each specifically designed to address a particular class of issues or dataset. The investigation of prevalent components within evolutionary processes is frequently conducted through the utilization of evolutionary computing as an in silico experimental methodology in the field of evolutionary biology.

In the context of natural evolution, populations exhibit a drive to optimize their fitness with the goal of increasing their likelihood of survival. This concept has been influential in the advancement of computer technology. AI systems aim to simulate the processes of emergence, survival, and refinement observed in human populations, with the objective of emulating their capacity to adapt to various environmental conditions. Genetic Decision issues are frequently encountered scenarios where algorithms, specifically genetic algorithms (GA), are commonly employed. Once a population is introduced, successive generations engage in communication and exert mutual influence to adapt to their environment. The flowchart presented in **Fig 2** provides a comprehensive representation of the operational sequence of a Genetic Algorithm (GA) at a higher level. At time t=0, a target is selected through a random process, and a population of finite size is initiated. Individuals are evaluated based on their alignment with the established criteria and are assigned a fitness rating that indicates their level of compatibility within the ecosystem.

The likelihood of reproductive success and gene transmission to subsequent generations is positively correlated with higher levels of individual fitness. Even individuals with limited physical or emotional strength have the potential to assume the role of parents. The population is rapidly increasing increase until either the termination condition is accomplished or the specified amount of generations has been attained. The overall population experiences a gradual enhancement in both physical well-being and cognitive abilities. Scientists utilize the techniques of crossover and mutation as means to enhance the population. For the process of crossbreeding to take place, it is imperative that specific individuals engage in the exchange of genetic material. Mutation induces subtle alterations in specific segments of an organism's genetic code.

Intelligent Agents for Intelligent Decision Support

The class of agents, which encompasses intelligent agents (IA) as described by Gizzi, Nair, Chernova, and Sinapov [21], is widely regarded as the most intellectually advanced among various artificial intelligence (AI) methodologies due to its exceptional aptitude in addressing decision problems. According to Yang, Chen, and Yang [22], an agent could be illustrated as an entity, which exists in a particular system, is found in a certain environment, and possesses the ability to independently act within this environment with the purpose of achieving its designated objective. Humans possess an inherent capacity to engage in action or make decisions based on contextual factors, in contrast to the normative reasoning observed in computer systems that employ if-then logic. In scholarly discourse, the different between an intelligent agency and an agent is elucidated through the utilization of the concepts of strong and weak agencies, as outlined by Korosec-Serfaty, Sénécal, and Léger [23].

Strong agency encompasses various qualities such as independence, promptness, flexibility, initiative, and social competence. Robust agency plays a crucial role in promoting various cognitive processes such as interaction, persistence, movement, reasoning, and education. The term "autonomous" refers to the state of being liberated from external influences or constraints. Agents possessing these attributes demonstrate a heightened sensitivity to their surroundings and possess the capability to make suitable adaptations. Proactive individuals with an inclination towards taking initiative are characterized by their proactive approach in assuming leadership roles to achieve their desired objectives. Agents who possess this capability have the potential to collaborate and synchronize their actions with each other. The ability to communicate with others gives rise to two distinct actions, namely cooperation and bargaining. The agent possesses the dual characteristics of mobility, enabling it to relocate to the necessary work location or where information is located, and persistence, allowing it to sustain its current state over an extended duration.

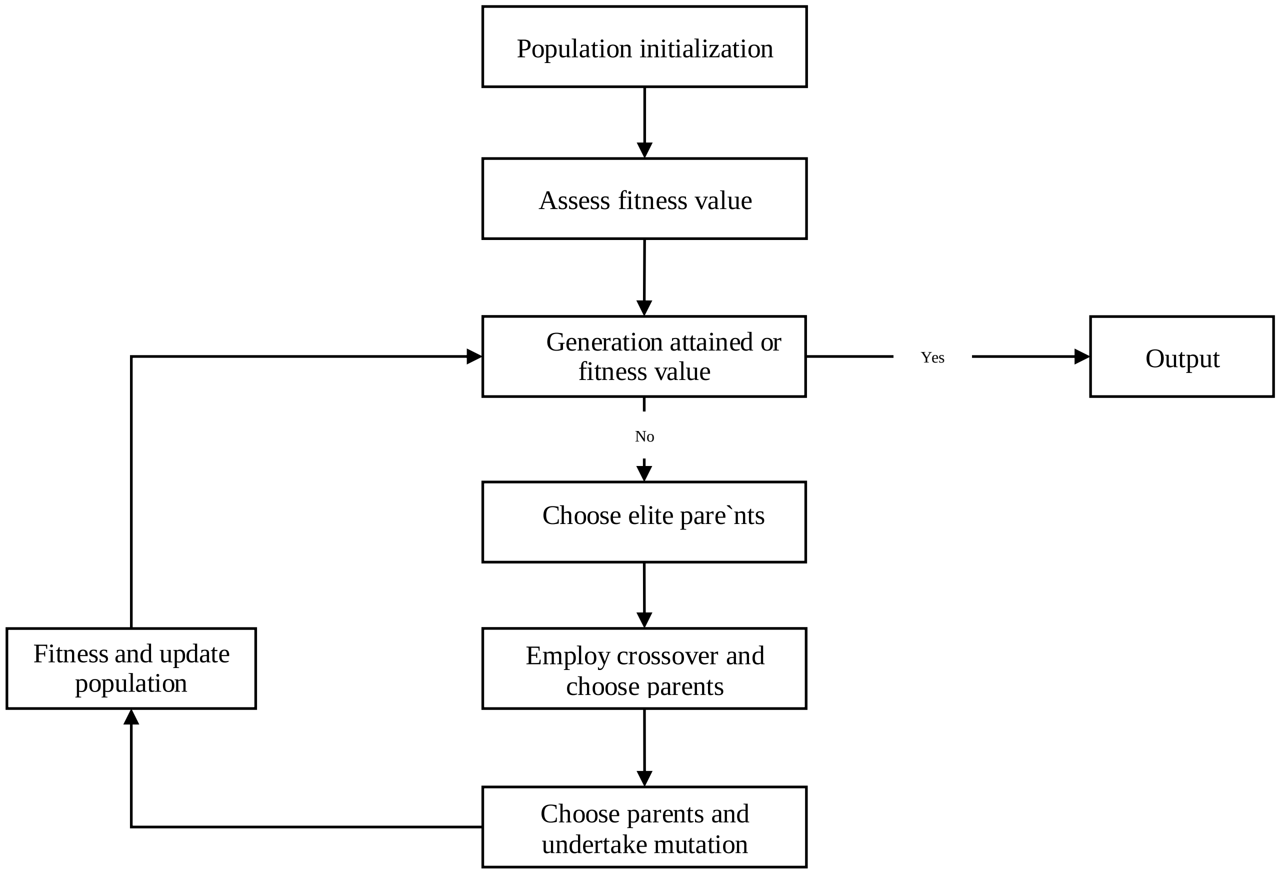

Fig 2. General Diagram for a Genetic Algorithm

The ability to engage in logical thinking and acquire knowledge suggests that an artificial intelligence (AI) has the capability to modify its actions in light of novel information or encounters. The manifestation of intricate behaviors in intelligent agents is often attributed to the utilization of human conceptual frameworks such as knowledge, intention, and beliefs in the explanation of their functioning. The development of Multi-Agent Systems (MASs) that operate with agent teams lacking complete information regarding the environment or other agents is a robust strategy for facilitating decision-making in challenging situations. According to Madni, Madni, Sorensen, and Garcia [24], individual agents (IAs) possess distinct characteristics that are programmed into them, and they have the ability to work together in order to achieve objectives as a collective. In order to achieve their goals, agents may be required to engage in various activities such as communication, collaboration, negotiation, knowledge acquisition, and even reliance on one another.

The Monetary Authority of Singapore (MAS) has the capacity to provide recommendations to individuals responsible for making decisions, or alternatively, they can assign agents with the power to initiate actions without requiring additional human intervention. The examination of the decision problem's representation, the team's size, and the capacity to restructure the team as required for problem-solving are all subjects of investigation within the field of Multi-Agent Systems (MAS). The Multilevel Adaptive Systems (MAS) framework demonstrates a high level of effectiveness, particularly in environments characterized by constant change and unpredictability. Groups of agents have the capability to observe their environment, adapt to unfamiliar situations, combine their knowledge, and agree on a collaborative plan of action. According to Yokoyama, Luo, Batra, and Ha [25], Agents can undergo training through different methods, such as supervised learning, unsupervised learning, and reward-based learning. In the context of supervised learning, such as in the case of neural networks, the system is directed by precise output values. Unsupervised learning involves the absence of provided outcomes, thereby necessitating the system to autonomously identify patterns within the dataset. Reward-based learning in the MAS is influenced by either positive or negative reinforcement.

DSS/IDSS evaluations should employ a comprehensive set of criteria in order to offer valuable feedback that can be utilized to enhance subsequent iterations of the system. Several studies have employed multi-criteria assessment in the context of DSS, as evidenced by the work of Razmak and Aouni [26]. Additionally, this approach has been explored in relation to various other categories of information systems, as demonstrated by the research conducted by Caroleo et al. [27]. The establishment of a connection between information systems and their users is a key aspect. To analyze the tradeoffs between performance and objectives, Deb [28] utilized a multiple-goal programming technique. In the study conducted by Hao, Nazir, Gao, Ma, and Ilyas [29], a multi-criteria approach was employed to incorporate these concepts into DSS and expert systems. This approach encompassed subjective, technical, and empirical methodologies. Subjective criteria included the opinions of users and sponsors, while technical criteria encompassed analytical methodologies and accuracy.

Empirical criteria involved conducting side-by-side comparisons of results with and without the system. Furthermore, Pillet, Carillo, Vitari, and Pigni [30] employed two primary forms of performance evaluation to assess information systems, namely effectiveness and efficiency. Sangoju, Kanchanadevi, Sivasubramanian, and Ramanjaneyulu [31] employed a set of three criteria to assess the performance of a system. These criteria include general systems principles, which are used to evaluate the extent to which the make a significant contribution to the accomplishment of objectives. Efficiency is another criterion used to measure the effectiveness of the transformation of inputs and resources into desired outcomes. Lastly, efficacy is employed to evaluate the system's capability to actually produce the desired results. Successfulness can be understood as a stance that is driven by values. According to Muscat et al. [32], the utilization of DSS has a significant influence on both the process and outcomes of decision making. Shalabi [33] conducted a study in which they observed that DSS applications from different origins were assessed by either focusing on the process of decision-making or a definite decision itself.

Qualitative process criteria frequently encompassed methodological enhancements, including increased efficiency, a systematic approach, a comprehensive understanding of the subject, the capacity to generalize findings, and expedited decision-making. Profitability, efficiency, predictability, and the capacity to anticipate failure were among the quantitative measures employed to assess the results. Consequently, there exists both theoretical and practical justification for the assessment of IDSS through the utilization of multiple criteria.

V. MULTI-CRITERIA FRAMEWORK FOR IDSS ASSESSMENT

The field of operations research has undergone advancements to encompass the domain of multiple criteria decision-making (MCDM). MCDM is primarily concerned with the enhancement of mathematical and computational instruments, which assist decision makers in their subjective assessment of the general performance criteria. Numerous research endeavors have been undertaken to advance the domain of MCDM. Over the past few years, Wu, Liao, Lev, and Zavadskas [34] have employed MCDM applications and instruments to mitigate local challenges such as environment, and sustainability, energy, supply chain management, quality management, material, GIS, project management, construction, safety and risk management, technology and information management, manufacturing systems, operational research, soft computing, production management, tourism management, and strategic management.

Since the 1960s, the domain of MCDM has experienced significant growth, leading to the publication of numerous books and papers that encompass both theoretical and practical aspects. The objective of MCDM methodologies is to ascertain a favored alternative, categorized alternatives into restricted group of categories, or/and prioritize alternatives according to subjective preference. When faced with numerous conflicting criteria, the various methods available to aid individuals in making choices aligned with their preferences are commonly known as MCDM approaches. The utilization of MCDM can be regarded as a systematic approach to address complex problems by breaking them down into more manageable components.

The individual components are reassembled in order to equip decision makers with a comprehensive overview, taking into account multiple factors and decisions made regarding smaller elements. The primary emphasis of most MCDM approaches lies in the examination of discrete alternatives that possess distinct characteristics based on a predefined set of criteria. The values of the criteria may be represented using either ordinal or cardinal values. The determination of information can vary in terms of precision, ranging from precise to fuzzy, and may evolve over time. Modern MCDM techniques enable decision-makers to effectively manage various types of information mentioned above. The selection of the combination method for addressing the decision issue is a prominent concern that emerges during the MCDM process. Nevertheless, multiple criteria decision analyzers provide various aggregation techniques.

In recent decades, there has been a significant increase in the prominence of all major categories of MCDM. Evaluation theories encompass assumptions pertaining to values or preferences, as well as structured depiction of these preferences or values. Formal models encompass a range of algorithmic frameworks, procedural methodologies, and paradigms for decision-making. The assessment approaches in MCDM scenarios include the techniques of scaling, estimation, and elicitation to determine the preference, subjective probabilities, and utilities of individuals. There is no prescribed methodology with explicit sequential instructions that individuals can adhere to throughout the entirety of a decision support process. The issue of aggregation poses a notable challenge when confronted with entities that can solely be characterized and evaluated based on a limited set of attributes. The objective is to perform a synthesis of the frequently conflicting characteristics of the objects with the purpose of carrying out tasks such as object selection, object ranking, object categorization, and similar activities. The available research indicates that the evaluation criteria for IDSS should consider both the process of decision making and its outcomes.

The Analytic Hierarchy Process (AHP), as projected by Nahavandi, Homayounfar, and Daneshvar [35], can be employed to establish a quantitative framework to assess the "decision value" of an Intelligent Decision Support System (IDSS), as discussed by Revathi, Anitha, and Hemanth [36]. AHP offers the advantage of facilitating the identification of distinct contributions made by multiple subcomponents. The statistical relevance of these contributions can be evaluated by employing a stochastic augmentation of the AHP as projected by El Hadidi, Meshref, El-Dash, and Basiouny [37]. The AHP provides a more systematic methodology for evaluating various options by structuring criteria in a hierarchical manner that is pertinent to the framework or the decision-making issue at hand. The AHP hierarchy, akin to a reporting diagram employed by organizations, facilitates the hierarchical structuring of pertinent criteria, wherein higher-level criteria are systematically refined into lower-level criteria.

The Analytic Hierarchy Process (AHP) facilitates the computation of intermediate comparisons and subsequently integrates them to generate decision value for contrasting alternatives at the highest level. Consequently, the assessor is only required to provide pairwise comparisons of alternatives at the lowest level. In situations where there exist multiple possibilities, it becomes necessary to assign weights to criteria and employ an eigenvalue approach to effectively reconcile initial assessments. The AHP has been extensively employed for the analysis of decision-making challenges. Furthermore, it has the potential to be applied for the evaluation of IDSS in a broader context.

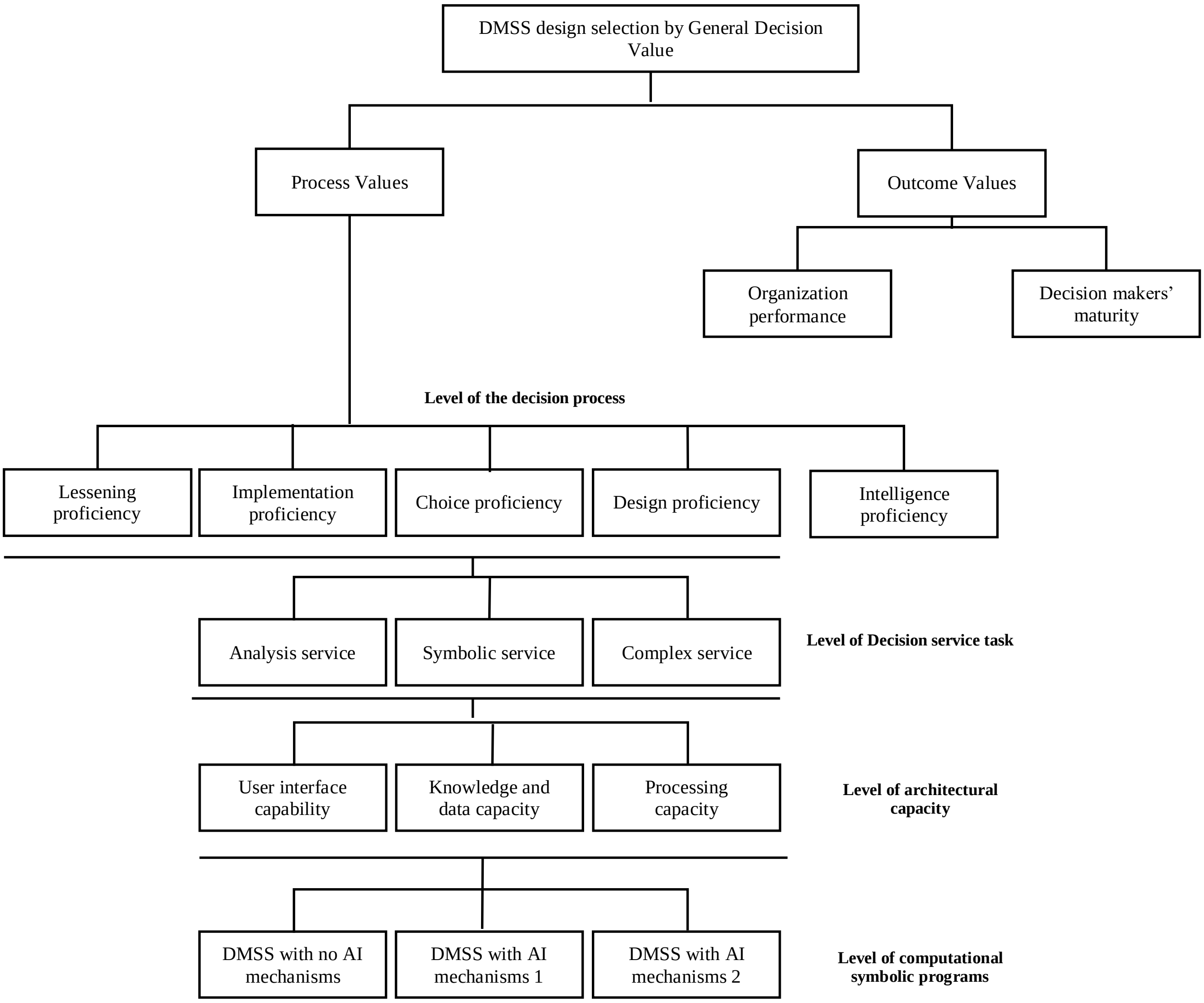

Fig 3. Multiple Criteria Models to Assess an IDSS

Fig 3 illustrates a proposed Analytic Hierarchy Process (AHP) analysis of a generic Intelligent Decision Support System (IDSS). The purpose of the hierarchy is to establish a correlation between the computational methodology employed to address a decision problem and the decision utility of an IDSS. The IDSS architecture facilitates the transmission of decision-making tasks, specifically those involving analysis, synthesis, and complexity, from the computational level. This transmission occurs through various components of the architecture, including the data, user interface, processing capabilities, and knowledge capabilities. Decision-making tasks are responsible for updating the process level. The determination of the result level is contingent upon the decisionmaker, who articulates the specific outcomes that are to be assessed. The determination of the decision value for the options presented at the foundational level is achieved through the amalgamation of both the process value and the outcome value. The illumination of an IDSS's design and the identification of improvement opportunities can be achieved through the application of multi-criteria assessment, thereby enhancing the effectiveness of decision-making support.

VI. CONCLUSION

Currently, there exist three main domains of inquiry pertaining to the potential utilization of artificial intelligence (AI) for decision support. Interfaces such as virtual humans have the potential to enhance the effectiveness of human-machine interaction. Additionally, techniques that are applicable to challenging applied problems, such as big data, can be employed. Furthermore, smart adaptive systems have the capability to modify themselves in order to address complex problems or cater to the preferences of individual users. The progress in computing and storage technologies has facilitated the accumulation of extensive quantities of information and data. This data can be effectively employed as a basis of decision-making in various domains, including finance, retail, online user profiles, and healthcare. The norm encompasses challenges that are characterized by their complexity, imprecision, loudness, dynamism, and unpredictability. The crucial factor for achieving success in the application of the most suitable artificial intelligence (AI) technique or combination of techniques (hybridization) to a specific problem domain lies in the process of adaptation.

The three levels that determine intelligent adaptive system utilizing intelligent approaches can be conceptualized as adaptation to a rapidly transforming ecosystem, adaptations to the same environment without direct porting and adaptations to an unknown or novel situation. In the context of financial decision-making, particularly in algorithmic trading within the stock market, the provision of real-time decision assistance becomes imperative due to the dynamic nature of the market and the extensive amount of data available for analysis. Another application of the ability to generalize from specific instances is the identification and timely alerting of credit card fraud, utilizing historical data. Unfamiliar or novel challenges pose the greatest difficulty in terms of finding solutions. Various approaches are employed by individuals to address such challenges, encompassing the utilization of historical precedents, expert perspectives, and contextual factors. Emerging systems are currently being implemented in specific domains; however, their applicability across broader categories of problems has not yet been established.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Ethics Approval and Consent to Participate

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Competing Interests

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