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Review

Decision-Making in the Age of AI: A Review of Theoretical Frameworks, Computational Tools, and Human-Machine Collaboration

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Abstract: Decision-making, a critical process across all disciplines, is undergoing significant transformation with the integration of advanced computational techniques. This review examines the evolution of decision-making, from its theoretical foundations to the implementation of optimization algorithms, neural networks, and artificial intelligence (AI). The review first explores the contrasting paradigms of normative and descriptive decision-making theories. Normative theories propose ideal decision-making processes based on rational calculations, while descriptive theories aim to explain real-world human decision-making, often incorporating cognitive biases and heuristics. Subsequently, the review investigates optimization techniques focusing on neural networks and deep learning. These powerful tools enable machines to learn complex patterns from data, facilitating tasks such as classification, prediction, and decision-making. Various neural network architectures, including feedforward networks, convolutional networks, and recurrent networks, are examined, highlighting their distinctive strengths and limitations. The review further explores the integration of AI in decision-making processes, examining its impact on organizational structures and the inherent challenges of human-machine collaboration within uncertain environments. While AI excels at analyzing vast datasets and identifying patterns, human judgment remains indispensable for strategic decisions, particularly in areas requiring implicit knowledge, ethical considerations, and navigating complex uncertainties. The review concludes by examining the ethical implications of AI-driven decisions and explores the potential for a future where AI effectively augments human capabilities. The need for AI literacy, transparency, and a thoughtful approach to integrating AI into decision-making processes is emphasized, aiming to maximize its benefits while mitigating risks. The review highlights the emergence of human-AI partnerships, where AI enhances human capabilities. Still, human oversight and judgment remain critical for navigating the complexities of strategic decision-making in a world marked by increasing uncertainty.

Keywords: decision-making, artificial intelligence (AI), neural networks, optimization techniques, human-AI collaboration, organizational impact

MSC: 90B50, 68T05, 91B06

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1. Introduction

Decision-making can be described as the process of choosing a course of action from a set of options. These options range from selecting a marriage partner to a political party affiliation. Researchers from various disciplines have shown interest in studying decision-making, particularly economics and psychology. Early decision-making models were mathematical, portraying the process as a series of calculations involving probabilities and monetary values of potential outcomes to determine the optimal choice. Many contemporary models of decision-making are adaptations of these initial mathematical approaches. Recent perspectives on decision-making place a greater emphasis on psychological factors. Among these are relatively stable personal characteristics known as individual differences. Numeracy, or the ability to understand and work with numbers, is a well-known example of a particular difference that impacts the quality of financial and health-related decisions. Another significant factor is intelligence or cognitive ability. Additionally, emotion has garnered considerable attention, particularly in dualprocess theories that differentiate between emotional and deliberative decision-making. Memory process models are also gaining influence in decision-making research, highlighting how people recall the features of options that can shape their preferences. Neuroscience has emerged as a valuable tool for uncovering the mental processes underlying these preferences and choices across these and other areas. The main goal of multi-criteria decision-making (MCDM) methods is to support decision-makers in choosing the optimal option from a set of alternatives while meeting specific criteria. Here, "alternatives" refer to the available options, and "criteria" denote the constraints or factors influencing the decision process. Giving adequate attention to multiple criteria is essential for accurate decision-making. MCDM techniques are precious for complex issues with numerous possible solutions, where the decision cannot simply be a yes or no. These methods enable comparing, assessing, and categorizing a limited set of alternatives based on a defined set of attributes. However, decisions made by individuals can often lack consistency, posing a risk in MCDM problems. Researchers have developed various MCDM methods to enhance decision-making accuracy and address this. This has led to the proposal of numerous research articles featuring new algorithms and mathematical tools to find more accurate optimal solutions. Previous research has largely concentrated on decision-making processes within specific industries, often examining them in isolation. This narrow focus has left a gap in understanding how decision-making frameworks can be applied more holistically across different domains. To address this limitation, our study explores decision-making structures and methodologies from an integrated perspective, incorporating artificial intelligence and a range of optimization techniques. By synthesizing these elements, we aim to uncover new insights into how decision-making can enhance overall system effectiveness and operational efficiency. This research not only broadens the scope of decision-making analysis but also provides a more comprehensive framework for leveraging advanced technologies to drive strategic improvements across various sectors. The following sections of the article are structured: Section 2 describes the methodology used in the article; Section 3 discusses various approaches to decision-making techniques and structures; Section 4 examines optimization techniques and their integration with decision-making; Section 5 explores the role of neural networks in decision-making; and Section 6 addresses the integration of AI in decision-making, focusing on human collaboration, challenges, and organizational structures.

2. Methodology

To enhance the validity and reliability of our review findings, we utilized a systematic literature review approach informed by Pittway's [1] ideologies: pellucidity, precision, assimilation, emphasis, impartiality, approachability, and handling. Following these guidelines involved setting a defined review scope (handling), formulating a precise research question (emphasis), providing justification for search terms (pellucidity), establishing, and documenting explicit inclusion and exclusion criteria (precision), choosing databases that ensure balanced and accessible representation of current research (impartiality and approachability), and assimilating findings to achieve a cohesive synthesis. The criteria for selecting articles for the review manuscript are presented in Figure 1.

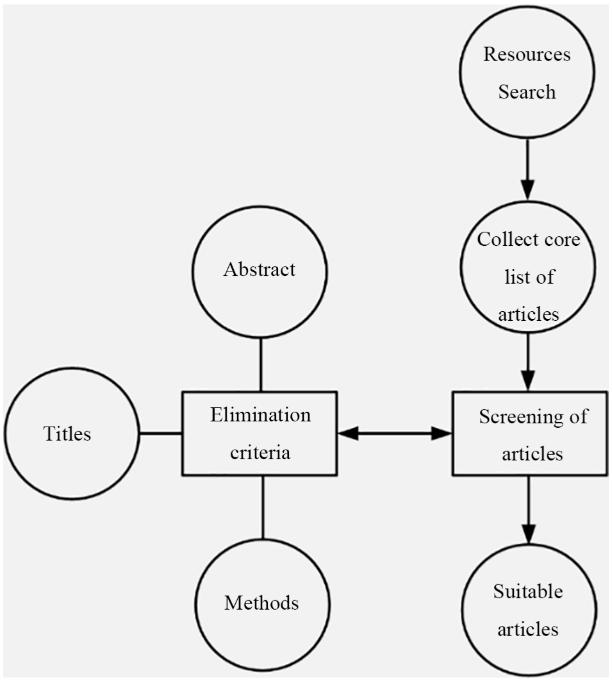

Figure 1. Criteria of article selection for review

The literature search was conducted across multiple databases, including Web of Science Core Collection (WoSCC), Scopus, ScienceDirect, and Google Scholar. These databases were selected to ensure comprehensive coverage of the literature, leveraging the rigorous indexing of WoSCC and Scopus alongside the broad interdisciplinary scope of ScienceDirect and Google Scholar. Next, the collected articles are screened based on specific criteria, including abstracts, titles, and methodologies, to remove irrelevant studies. Relevance of Title-Articles with titles that do not align with the research objectives or key themes (e.g., decision-making, AI integration, optimization techniques) are excluded based on the following criteria.

• Abstract Content: Studies that, based on their abstracts, lack a clear connection to the research focus or do not contribute to the understanding of integrated decision-making approaches are removed.

• Methodological Rigor: Articles that do not employ a well-defined methodology, lack empirical validation, or do not use relevant AI or optimization techniques are excluded.

• Duplication: Duplicate studies or papers with overlapping content from the same authors are eliminated to avoid redundancy.

• Publication Type: Non-peer-reviewed sources, opinion pieces, editorials, and incomplete conference abstracts are excluded to ensure the inclusion of high-quality, credible research.

The literature search was conducted using the Boolean operator 'AND' to combine the following keywords: 'Decision Making', 'Artificial Intelligence', 'Neural Networks', and 'Computational Tools'. The logical expression used in the search query was: ("Decision Making", "Artificial Intelligence", "Neural Networks", AND "Computational Tools"). This ensured that the retrieved studies explicitly addressed the intersection of these concepts, aligning with the focus of our research. These keywords were chosen to ensure a comprehensive selection of studies relevant to the research focus, covering various aspects of decision-making processes, AI-driven methodologies, and advanced computational techniques. The remaining articles are then assembled for the review. A total of 119 articles were selected for review, while additional articles were cited to describe the architecture and structure of decision-making.

The literature search was conducted across four major databases: ScienceDirect, Google Scholar, WoSCC, and Scopus. Specifically, the paper divided the literature search into distinct sections based on the database used. The results from each database were analyzed separately to assess the variations in coverage and focus.

• WoSCC: This database yielded 27 relevant studies, with a primary focus on peer-reviewed journal articles and conference proceedings related to decision-making, AI integration, and neural networks. These studies were rigorous, high-quality, and directly aligned with the core themes of the review.

• Scopus: Scopus returned 23 studies, with an emphasis on AI-driven decision-making models and optimization algorithms. The studies from Scopus were similar in quality to WoSCC, but the database also included a notable number of interdisciplinary articles that connected AI to broader fields such as healthcare and engineering.

• ScienceDirect: ScienceDirect provided 45 studies, highlighting optimization techniques and AI applications in decision-making. This database included a wider range of conference papers and industry reports, offering diverse methodological approaches but a slightly broader scope than WoSCC or Scopus.

• Google Scholar: Google Scholar returned 24 studies, offering a more diverse set of articles, including grey literature, technical reports, and non-peer-reviewed content. While the inclusion of these less curated sources expanded the breadth of the literature, it also resulted in a less rigorous selection of studies.

The comparison of results across these databases revealed that WoSCC and Scopus provided more focused and high-quality results, offering in-depth coverage of AI-driven decision-making models and optimization techniques. To address observed inconsistencies in the results across the four databases, we investigated the retrieval patterns WoSCC, Scopus, ScienceDirect, and Google Scholar for the 119 articles selected in this review. Google Scholar retrieved the highest number of papers (24 articles), consistent with its inclusive, crawler-based approach that indexes journals, conference proceedings, theses, books, and unpublished works, often exceeding the curated collections of WoSCC (27 articles) and Scopus (23 articles). The difference between WoSCC and Scopus primarily arises from WoSCC's inclusion of the Emerging Sources Citation Index (ESCI), which covers emerging journals and conference proceedings not yet fully indexed in Scopus; for instance, 5 of WoSCC's unique articles were from ESCI-indexed conference proceedings absent in Scopus. Surprisingly, ScienceDirect yielded the greatest number of references (45 articles), despite its journals typically being indexed in Scopus and/or WoSCC. This anomaly is not solely attributable to its search engine but rather to its broader inclusion of interdisciplinary conference papers and industry reports (e.g., 12 unique items) alongside journal articles, which are not always prioritized in WoSCC or Scopus searches due to their selective criteria. ScienceDirect's retrieval was further amplified by its permissive search interface, which captured a wider range of document types within our Boolean query. These findings suggest that while ScienceDirect journals overlap with Scopus and WoSCC, their higher count reflects a combination of unique content and search engine sensitivity, highlighting the need for multi-database approaches to capture the full scope of relevant literature. On the other hand, Google Scholar and ScienceDirect captured a broader range of studies, including interdisciplinary and non-peer-reviewed content, enriching the literature with diverse perspectives. This multi-database approach ensured that the literature review covered both highly specialized research and broader interdisciplinary insights. Given that this review was conducted up to February 21, 2025, we note that no papers from 2023 to early 2025, directly addressing the intersection of decision-making, artificial intelligence, neural networks, and computational tools within our specialized scope, were identified across all four databases searched: WoSCC, Scopus, ScienceDirect, and Google Scholar. This observation reflects the time frame of our literature retrieval and screening process, which concluded before the full publication cycle of 2025 could be captured. While some databases, such as WoSCC and Scopus, offer rapid indexing of recent articles, and Google Scholar includes preprints, the absence of directly relevant studies from this period across all sources may suggest either a lag in publication or a shift in research focus. Nonetheless, our sample of 119 articles, spanning earlier years, provides a robust foundation for synthesizing current knowledge in this field, with future updates potentially incorporating emerging 2025 contributions.

To further enhance the robustness and transparency of our systematic review, we analyzed the 119 selected articles using statistical tools available in WoSCC and Scopus. This analysis provides insights into the geographical distribution, disciplinary fields (based on JCR/SJR categories), and publication sources of the reviewed literature, enriching the paper with a comprehensive overview of its scholarly foundation.

• Geographical Distribution: Figure 2 illustrates the geographical origins of the articles based on the corresponding authors' affiliations. The United States leads with 32 articles (26.9%), followed by China (21 articles, 17.6%), the United Kingdom (12 articles, 10.1%), Germany (9 articles, 7.6%), and India (7 articles, 5.9%), with other countries contributing the remaining 38 articles (31.9%). This distribution reflects a strong North American and Asian research presence, underscoring the global interest in AI-driven decision-making.

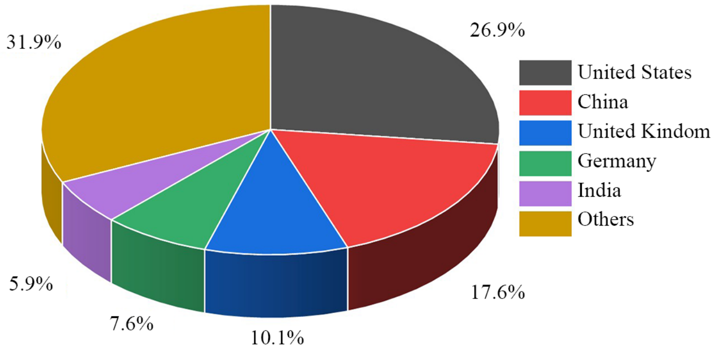

Figure 2. Geographical distribution of reviewed articles showing the number of articles per country

• JCR/SJR Fields: Figure 3 categorizes the articles by their journal citation reports (JCR) and scimago journal rank (SJR) fields. Computer Science dominates with 48 articles (40.3%), followed by Engineering (25 articles, 21.0%), Decision Sciences (18 articles, 15.1%), and Business/Management (14 articles, 11.8%), with other fields like Medicine and Social Sciences contributing 14 articles (11.8%). This breakdown highlights the interdisciplinary nature of decision-making research, bridging technical and managerial domains.

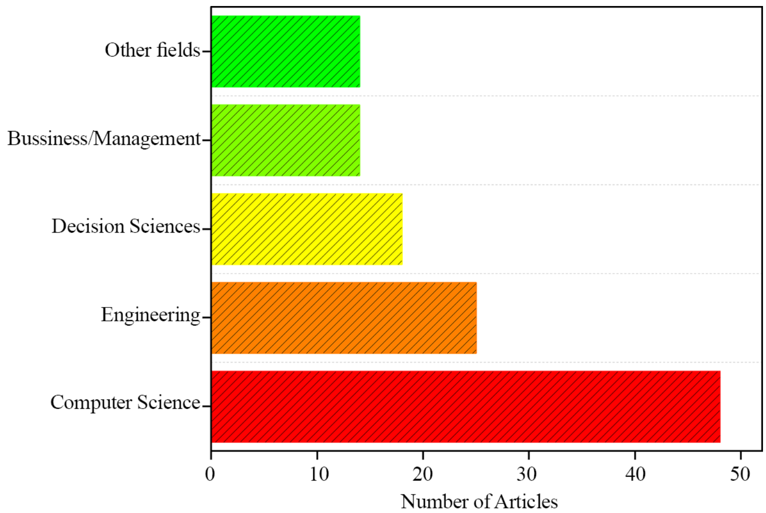

Figure 3. Distribution of articles by JCR/SJR fields depicting percentages

• Publication Sources: Figure 4 shows the distribution of articles across journals and conferences. Top journals include 'IEEE Transactions on Neural Networks and Learning Systems' (9 articles), 'Decision Support Systems' (7 articles), and 'Artificial Intelligence' (6 articles), collectively accounting for 22% of the sample. Conference proceedings, such as those from IEEE and ACM, contribute 28 articles (23.5%).

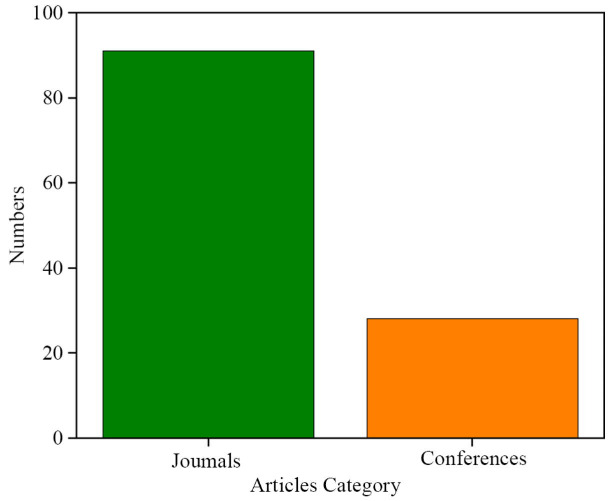

Figure 4. Distribution of articles by publication type comparing journals

Figure 5 details the top 10 publication sources, emphasizing the prevalence of high-impact, peer-reviewed outlets.

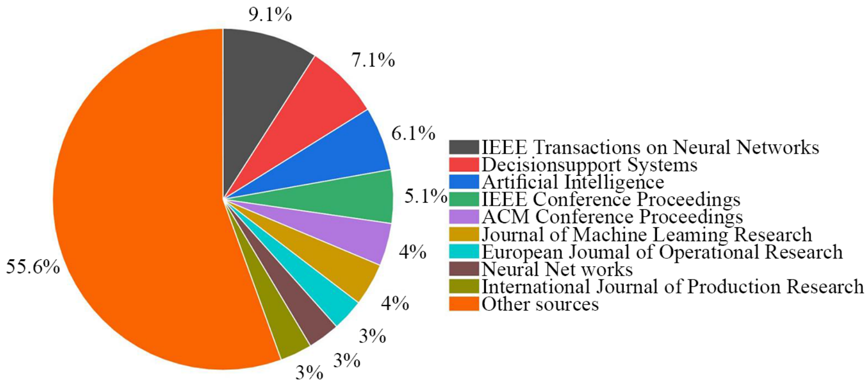

Figure 5. Top 10 publication sources listing specific journals/conferences

These graphical representations (Figures 2-5) complement the textual analysis by visually summarizing the literature's scope and quality. The predominance of Computer Science and Engineering reflects the technical focus on AI and neural networks. At the same time, the inclusion of Decision Sciences and Management underscores the practical implications for organizational decision-making. The reliance on reputable journals and conferences ensures the credibility of the reviewed studies, adding value to our synthesis.

3. Approaches

The decision-making literature presents various theoretical frameworks, primarily the normative and descriptive approaches. Normative theories focus on how individuals should make decisions, often detached from real-world scenarios or empirical evidence. In contrast, descriptive theories examine how people make decisions in real-life situations, whether rationally or not, and are grounded in empirical research. In recent years, descriptive theories have gained greater prominence, often overshadowing normative perspectives. This shift has resulted in a growing divide between the two approaches. The following sections will provide a more detailed exploration of both normative and descriptive theories, as illustrated in Figure 6.

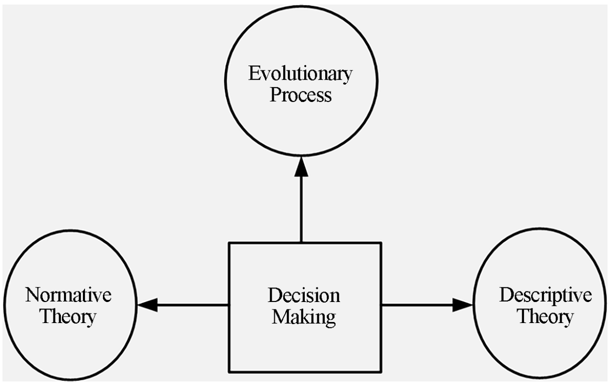

Figure 6. Various approaches to decision making

3.1 *Normative theory*

Normative theories of decision-making take a prescriptive, top-down approach, offering guidelines on how individuals ought to make decisions. These theories are built on mathematical analyses aimed at identifying optimal choices [2–5]. The aim is to learn how to make optimal choices by developing algebraic models of preferences grounded in idealized behavioral principles [6]. Normative guidelines serve as rational benchmarks to assess actual behavior [7], helping individuals maximize the expected utility of their choices [8]. Recent advancements in decision-making and artificial intelligence have been discussed extensively in various studies [9, 10]. More recent studies have emphasized the groundbreaking exploration of contrasting paradigms between normative and descriptive decision-making theories [11, 12]. Normative theories present ideal decision-making processes based on rational calculations, while descriptive theories focus on explaining how people make decisions in the real world [13, 14]. These theories often account for cognitive biases and heuristics, which are incorporated into AIbased models, particularly neural networks, and computational tools, to optimize decision-making processes [15]. Within this framework, decision-making is viewed as a problem-solving progression centered on enlarging predictable utility across different possibilities for the dissemination of outcomes [6]. Rooted in Expected Utility

Theory (JC das Neves), this approach relies on fundamental axioms such as transitivity, cancellation, dominance, and invariance. Decision-making, in this context, entails choosing from a range of possible actions [16]. Under conditions of risk and uncertainty, individuals evaluate their options based on expected utility. They anticipate the consequences of each action and assign a probability to each potential outcome (i.e., expected utility). This process requires reasoning in probabilistic terms, assessing the utility of each choice, and evaluating the likelihood of each outcome occurring [17]. Ultimately, the substitute that suggests the greatest benefit with the least risk is chosen to reduce uncertainty. Research has revealed that decision-making strategies frequently deviate in predictable ways from the principles of normative models [18]. In real-life situations, decisions are often made with incomplete or irrelevant information. For example, the outcomes of available options may constantly change. Furthermore, normative models overlook the cognitive demands involved in the decision-making process.

3.2 *Descriptive theory*

Specified the normative approach's shortcomings, decision-making research has increasingly devoted itself to procedures that can be more undoubtedly witnessed in experimental settings [19]. Its aim is to explain why people often deviate from the predictions of rational choice theory, suggesting that human decisions are more adaptive and context dependent. To address the failures of expected utility theory, Kahneman and Tversky developed prospect theory [20], showing that individuals tend to take more risks when decisions are framed as losses but become more risk-averse when decisions are framed as gains, even if both choices have equal value.

Prospect theory divides the decision-making process into two stages: an initial "editing phase" and a subsequent "evaluation phase". In the editing phase, individuals simplify and restructure options to make the evaluation phase more manageable. This phase modifies the prospects in ways that influence how choices are perceived. According to prospect theory, individuals interpret outcomes in terms of gains and losses, with these perceptions shaped by how the options are framed and the decision-maker's expectations [21]. Following this phase, the assessment starts, and the possibility with the greatest perceived value is selected. Prospect theory is based on two primary scales: the value scale and the decision weight scale. The value scale attributes subjective importance to the collective upshot, which is then compared to a reference point. Gains and losses are defined as deviations from this reference point, which is influenced by past experiences. Thus, the quality of prior decisions affects how new options are evaluated, as changes in value are relative to their opening theme [21].

The decision weight gauge, on the other hand, assigns a weightiness to each probability, indicating the extent of its influence on the total value of the options. This scale highlights the importance of events based on whether they are perceived as rare or common. Unusual events may be given disproportionately high decision weights or disregarded entirely [21]. (Conversely, events with a high likelihood of occurring are often assigned lower decision weights because they are seen as less significant Mishra). The final value of each outcome is calculated by multiplying its value by the decision weight. However, these weights are not actual probabilities and do not conform to rational decision-making principles. Instead, they reflect a subjective judgment of utility, helping individuals choose what they perceive to be the best option (Mishra). In our view, prospect theory demonstrates in what way capability influences the decision-making process, leading persons to seek satisfactory rather than optimal solutions, as finding the best solution often demands significant mental effort. In other words, decision-making in certain situations requires rarer cognitive effort than the ideologies outlined in Expected Utility Theory suggest [17].

3.3 *Evolutionary process*

Over the past few decades, research has consistently demonstrated that individuals frequently deviate from the principles of expected utility theory (Moreira). Similarly, studies in evolutionary and ecological fields indicate that human decision-making often diverges from the predictions of rational choice theory (Moreira). While cognitive abilities may be optimized for decision-making in stable environments, real-world scenarios are rarely static. Constant environmental changes necessitate adaptation, reinforcing the concept that human rationality is inherently bounded by cognitive limitations. However, in certain domains, these deviations are often perceived as irrational behavior. Such tendencies may be influenced by cognitive biases (Pronin), which have been observed in various species [22]. What initially appears as irrational can often be understood through ecologically rational decisionmaking, where decision rules evolve to align with dynamic environmental conditions over time [22]. These evolutionary perspectives provide valuable insights into understanding biases in decision-making and have significant implications for the development of artificial intelligence (AI). AI systems that aim to mimic or augment human decision-making must consider these adaptive mechanisms to enhance their functionality in real-world applications. Evolutionary findings highlight how decision strategies are shaped by dynamic and complex environments, offering a theoretical foundation for designing AI models that are not solely reliant on expected utility calculations but also incorporate heuristic-based decision frameworks.

Traditional decision-making models and experimental research often overlook crucial environmental factors, leading to inaccurate predictions and seemingly irrational behaviors. In many cases, the exhaustive analysis required by expected utility theory is impractical. Instead of seeking an optimal solution, individuals often settle for a "good enough" option, as computing the absolute best decision can be time-intensive and cognitively demanding [17]. Consequently, humans rely on heuristics-mental shortcuts or "rules of thumb"-to facilitate decision-making [23, 24]. These heuristics reduce cognitive effort compared to the complex computations required by utility models. In cognitive psychology, heuristics are recognized as effective, simplified decision-making strategies that help manage complexity and uncertainty [17]. In the context of AI, integrating heuristics into machine learning and decision-making algorithms can improve adaptability and efficiency. AI systems designed to support decision-making in uncertain and evolving environments-such as healthcare diagnostics, financial modeling, and crisis management (e.g., during the COVID-19 pandemic)-benefit from incorporating heuristic-based strategies. By understanding the evolutionary underpinnings of decision-making, AI can be developed to mirror adaptive human reasoning, making it more effective in real-world scenarios.

The intersection of evolutionary theory and AI-driven decision-making highlights the necessity of designing systems that account for cognitive limitations, environmental influences, and adaptive heuristics. By bridging these perspectives, AI can move beyond rigid optimization models toward more flexible and human-like decision-making processes, enhancing its applicability in diverse fields. As adaptive strategies, heuristics reduce the cognitive effort needed by deliberately ignoring some information [25]. Heuristics are essential in problem-solving and decisionmaking as they accelerate these processes [26]. However, they can also introduce errors and biased judgments. Heuristics operate within a fast, intuitive, often automatic, and subconscious information processing system, contrasting with a slower, more deliberate, accurate, and effort-intensive system [27]. This idea is captured in the Dual Process Concept of cognizance, spread by Daniel Kahneman [28], illustrated in Figure 7, which distinguishes between two modes of thinking: System 1 is characterized by speed, intuition, and automatic processing, while System 2 operates in a slower, more deliberate, and controlled manner. System 1 processes information quickly, often guided by emotions, and is less easy to control or adjust. In contrast, System 2 is systematic, analytical, and adaptable. System 1 effectively filters out unnecessary environmental information, supporting cognitive efficiency and assisting individuals in handling information overload [26]. On the other hand, System 2 steps in to correct and adjust for the biases and blind spots of System 1 [26]. Together, these systems reduce the cognitive effort required for decision-making and help optimize time, as System 1 typically performs its tasks effectively. However, as noted in Prospect Theory and the study of heuristics, System 1 is prone to systematic errors.

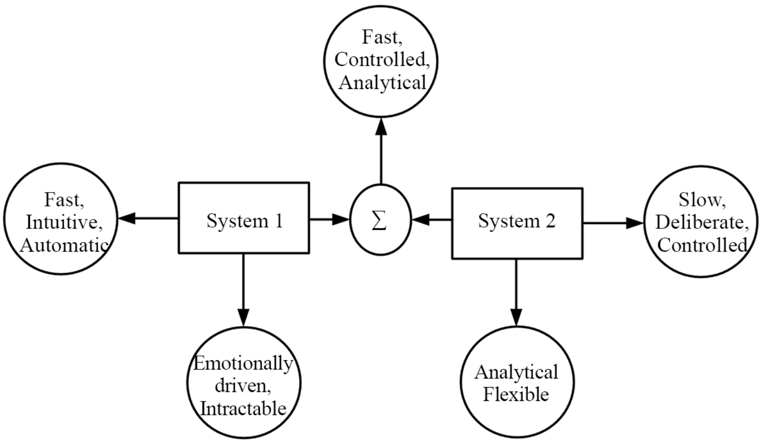

Figure 7. Illustration of dual-process theory of cognition

4. Optimization algorithms

The accuracy of any decision-making model largely depends on how well it assigns priority, weight, or relative importance to each component in achieving the decision objective. In this regard, MCDM methods offer a practical approach. These methods establish priority values or weights for different factors, distinguishing them based on their relevance to the decision objective. These evaluations are relevant in both ideal and less-than-ideal situations. Pairwise comparisons grow increasingly challenging when incorporating both qualitative and quantitative elements. MCDM methods in such cases are often called compensatory methods [29], where trade-offs between criteria are allowed. For instance, a product with high costs but exceptional sound quality may still be acceptable because the superior quality compensates for the higher price. On the other hand, non-compensatory techniques treat attributes as independent, with no room for trade-offs. For instance, obtaining a driver's license requires passing the applied driving assessment, the driving guidelines examination, and the eye test; each is compulsory and cannot be substituted for the others. To achieve optimal decision-making, the priority of parameters should always be set based on the best possible conditions. While MCDM methods can exploit differences in the influence or “impact” of components, they may not always stop the objective function from moving into invalid solution space. Yet when features are distinct, achieving the ideality of the criterion function is not always certain. To address the limitations of MCDM methods, optimization techniques (OTs) can be utilized to generate a collection of high-quality solutions, referred to as the Pareto-optimal front. MCDM can then be used on this group to select the best solution based on prioritized weightiness. The integration of MCDM methods with artificial intelligence (AI) enhances decision-making by leveraging machine learning algorithms to automate and optimize weight assignments dynamically. AI-based models, such as neural networks and reinforcement learning, can refine MCDM processes by predicting the relative importance of criteria based on historical data and contextual inputs. For example, AI-driven MCDM has been successfully applied in healthcare decision support systems, financial risk assessment, and smart city planning, where real-time data analysis helps prioritize competing objectives efficiently.

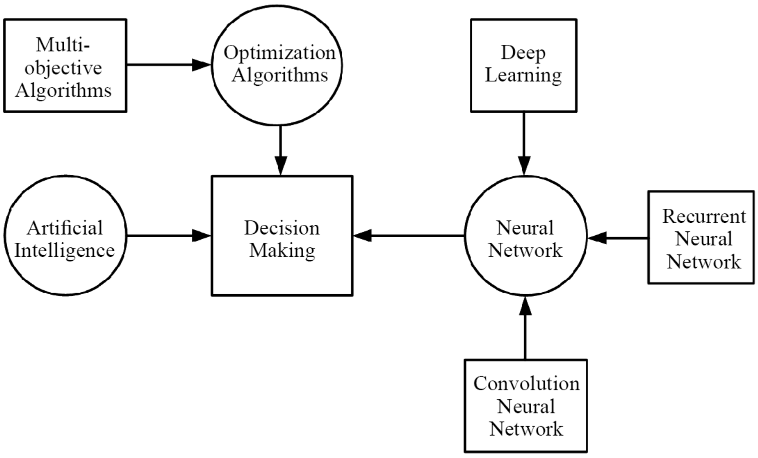

Figure 8. Incorporation of techniques in decision making

Furthermore, AI enables adaptive optimization, allowing MCDM techniques to adjust criteria weighting dynamically as new information becomes available. By incorporating AI, decision-making systems become more robust and responsive, ensuring that the selected solutions remain optimal even in fluctuating environments. Nevertheless, for OTs to be effective, at least one objective must be defined. This requires framing an objective function using the available factors, which is generally nonlinear and is created by applying a weighted ratio of favorable and unfavorable components. By integrating MCDM with AI-driven optimization, decision-makers can achieve more accurate, flexible, and data-driven outcomes, bridging the gap between traditional decision analysis and modern computational intelligence [30, 31]. OTs always yield priority values for each element in the optimal scenario, intended in standardized arrangement. Consequently, OTs normalize judgement variables, purposes, and constrictions. Due to this feature, some researchers prefer using OT followed by MCDM to ensure optimal decision-making. Essentially, OTs techniques can be classified into two types: conventional methods that provide meticulous solutions and heuristic approaches that offer estimated solutions. The Incorporation of optimization techniques in decision making is illustrated in Figure 8. This classification, with heuristic approaches like approximation methods and multi-objective algorithms (MOAs), primarily differs in the number of iterations used [30, 31]. While exact methods can provide a direct solution, they are not always feasible. In contrast, approximation methods reliably offer near-optimal solutions. Furthermore, MCDM methods can be divided into multi-attribute decision making (MADM) and multi-objective decision-making (MODM) approaches. MADM focuses on selecting the best alternative from a set of options, whereas MODM seeks to optimize multiple objectives simultaneously. MADM techniques are particularly vital in fields such as management and engineering, where decision-makers must choose the most suitable option from a limited pool of alternatives [32]. By design, MODM techniques treat criteria by means of constrictions and substitutes as purposes to formulate an optimization problematic. However, when nonlinear factors and numerous objectives are involved, this approach becomes increasingly complex. Traditional methods often fall short in managing these complexities. To overcome these challenges, researchers turn to MOAs, which can reliably produce near-optimal results despite not always yielding the absolute best solution.

These algorithms allow for efficient handling of many alternative solutions with minimal effort. In multi-objective optimization, algorithms based on populations and swarms generally offer dominance-guided solutions that may not be the absolute best options but are close to optimal. MCDM techniques are then employed to rank these solutions according to the decision-makers' preferences. In our opinion, this synergy between metaheuristic approaches and MCDM techniques results in more robust and effective decision-making processes. MOAs offer distinct advantages, primarily by significantly enhancing optimization outcomes.

These algorithms are based on leveraging the collective intelligence of individuals within a population [30, 33]. Their use has been instrumental in reducing costs, assigning resources, and optimizing routes [34]. Recent applications span diverse fields, including computer security, engineering, economics, and science [30]. However, determining the most effective MOAs remains an ongoing challenge. To enhance the quality of solutions, researchers often combine algorithms in hybrid approaches, allowing one to compensate for the limitations of another. MOAs are categorized into several types based on their core characteristics as presented in Table 1.

Table 1. Categories of multi-objective algorithms based on key features

MOA categories	Description	
Nature	Ant colony optimization, gravitational ant colony algorithm	[33–37]
Population	Particle swarm optimization, genetic algorithms, multi-verse optimizer	[30, 37–40]
Memory	Black widow optimization and coral reef optimization, imperialist competitive algorithm, and firefly algorithm	[36, 41–43]
Iterative	Heuristic optimization, monte carlo algorithms	[33, 34, 37, 39, 44]
Greedy	Metaheuristics optimization	[44]
Unique solution	Aquila optimizer, evolutionary algorithms	[35, 36, 39–41, 43]

5. Decision making along with the neural network

Neural networks represent a highly effective type of machine learning algorithm frequently used in decision-making applications [45]. Inspired by the human brain's architecture, they are developed to capture and interpret complex input-output relationships. Neural networks consist of interconnected neurons arranged in layers-typically comprising input, hidden, and output layers [46]. Each neuron processes incoming data applies a mathematical function and transmits an output to the next layer. One of the key advantages of neural networks is their capacity to learn from large datasets and generalize to new, unseen data. Through training, the network adjusts its internal parameters, or weights, to reduce the error between its predictions and actual target values. After training, neural networks can make predictions on fresh data, making them suitable for tasks like classification, regression, and pattern recognition. Various neural network architectures are utilized in different areas of decision-making devel-opment [47–50]. Feedforward neural networks (FNNs) represent a straightforward architecture, with data flowing unidirectional from input to output layers (Vijayakumar). Convolutional neural networks (CNNs), frequently employed in image in addition to video processing, are designed to capture spatial hierarchies through convolutional layers [51, 52]. Recurrent neural networks (RNNs), featuring recurrent connections, excel in handling sequential data by modeling temporal dependencies [53]. Neural networks have achieved outstanding success across a wide range of decision-making fields, such as natural language processing (NLP), computer vision, speech recognition, recommendation engines, and autonomous driving. Their ability to detect complex patterns and provide accurate predictions has made them essential tools in various industries. However, neural networks also present challenges, including high computational requirements, lengthy training durations, and the risk of overfitting, where models become overly specific to training data and struggle to generalize well. To mitigate these issues, methods like regularization and data preprocessing are frequently employed to improve model performance and resilience.

Neural networks are designed to learn from data by identifying complex patterns and relationships, allowing them to generate accurate predictions or conclusions. Their adaptability and ability to solve complex problems have made them a crucial tool in artificial intelligence. These networks come in various forms and are used across many industries. The FNN, also known as a multilayer perceptron, is the most basic neural network architecture and is widely applied to tasks such as classification, regression, and pattern recognition [54]. CNNs excel in image linked chores-including arrangement, item discovery, and dissection due to their capability to efficiently process visual data [55]. RNNs, which are planned to handle sequential data such as time series and natural language, are well-suited for modelling temporal dependencies thanks to their recurrent connections [56]. More advanced RNN variants, such as long short-term memory (LSTM) [57] along with gated recurrent units (GRU) [58] further enhance this ability by effectively managing long-term dependencies and overcoming the vanishing gradient problem [59]. Generative adversarial networks (GANs) utilize a unique structure, consisting of a generator and a discriminator that work in opposition to one another, leading to the generation of highly realistic synthetic data. This architecture has proven effective in chores such as unsupervised learning, data synthesis, and image generation [60]. Reinforcement learning (RL) networks, which conglomerate neural networks with RL algorithms, enable systems to learn over environmental interactions, making them particularly effective for decision-making chores involving tardy recompenses, such as those in gaming, robotics, and autonomous systems [61]. In our analysis, selecting a deep learning technique be influenced by on multiple factors, including data category, chore necessities, besides the necessity to capture patterns or relationships. Scholars and experts continue to explore different neural network architectures to advance AI capabilities and optimize decision-making, tailoring solutions to fit specific challenges. For forecasting tasks such as time-series prediction, financial market analysis, and demand forecasting, RNNs and LSTM networks are particularly effective due to their ability to model temporal dependencies. In classification problems, including medical diagnostics, image recognition, and text categorization, CNNs and FNNs excel in identifying spatial structures and extracting relevant features. When dealing with optimization challenges such as resource allocation, supply chain management, and automated control systems, deep reinforcement learning (DRL) and Evolutionary Neural Networks are valuable in learning optimal decision policies through iterative improvements. Beyond these widely adopted models, specialized architectures further enhance AI-driven decision-making. Transformer Networks are particularly well-suited for NLP-based decision-making and sequence modeling, deep belief networks (DBNs) excel in feature extraction and probabilistic reasoning, while self-organizing maps (SOMs) are effective for clustering and anomaly detection. Each of these architectures offers unique advantages, making them well-suited for specific data types and problem domains. The selection of the most suitable neural network architecture is ultimately driven by the characteristics of the data and the specific problem to be addressed.

5.1 *The constitute of deep learning*

Deep learning, a specialized branch of machine learning, focuses on data representation learning. At its core, Deep learning neural networks are fundamentally composed of interconnected processing and communication nodes analogous to those in biological systems. Foundational architectures in deep learning include CNNs, multilayer perceptron, restricted Boltzmann machines (RBMs), auto-encoders, and RNNs [62–64]. Multilayer perceptron's with auto-encoders represent a type of feed-forward neural network featuring multiple concealed layers, where a piece layer comprises a perceptron with varied activation functions. The auto-encoder, an unsupervised learning model, is designed to reproduce input data at the output layer. Using backpropagation, the network computes the gradient of the error function with respect to the weights in the network. In representation learning, a key task of the autoencoder is encoding inputs by compressing high-dimensional vectors into smaller representations that capture essential features, enabling processes like data compression, dimensional diminution, besides data rebuilding. CNNs, structured as feed-forward networks with convolutional layers, are designed to capture features at both local and global levels., enhancing predictive accuracy. Meanwhile, RBMs consist of a visible layer and a hidden layer, forming a two-layer neural network without intra-layer communication. RBMs effectively extract features and attributes using gradient descent approximations. Over the past few years, deep learning has been rapidly adopted by managers to improve decision-making processes across various organizational levels [65]. Applications of deep learning have also seen extensive use in the burgeoning field of social media, resulting in massive quantities of unstructured, user-produced media, including text, images, and videos [66]. These algorithms have become invaluable for analyzing and gaining intuitions from this intricate digital environment, commonly known as the "echoverse", comprising user content, organizational material, traditional news, and press releases [67]. Deep learning technologies thus play a critical role in processing the varied data within the echoverse, greatly boosting businesses' decision-making abilities.

5.2 *Application in decision making*

Deep learning, particularly through neural networks, has revolutionized numerous fields by enabling the processing of large datasets and the identification of complex patterns [68]. One of the most significant impacts has been in computer vision, where deep learning has redefined fundamental tasks such as object detection, facial recognition, and image classification, ushering in a new era of advancements [69]. By training on extensive datasets, these networks enable highly accurate visual-based decision-making, leading to revolutions in self-directed vehicles, reconnaissance structures, and medicinal copy investigation [70]. Their ability to identify and classify objects with precision has also driven progress in fields like agriculture and healthcare [71]. Beyond computer vision, natural language processing (NLP) has witnessed remarkable progress due to deep learning. Neural networks have demonstrated strong performance in tasks such as language translation, sentiment analysis, and question-answering [72–74]. These models power essential technologies, including chatbots, virtual assistants, and search engines, allowing for more sophisticated interpretation and response to textual data [75]. As a result, deep learning has significantly enhanced human-computer interactions, transforming how individuals engage with technology [71, 72]. Another major application of deep learning is in recommendation systems, where neural networks analyze user preferences and past interactions to deliver personalized suggestions. E-commerce platforms, streaming services, and social media networks leverage these models to enhance user experience, boost engagement, and optimize content delivery efficiency [76, 77]. In addition, deep learning has had a profound influence on financial decision-making. Neural networks excel at analyzing vast amounts of complex financial data, forecasting stock market trends, detecting fraudulent transactions, and supporting algorithmic trading and credit risk evaluation [78]. By identifying patterns within large datasets, these models facilitate dynamic decision-making, helping to mitigate risks and improve financial performance [79]. The applications of deep learning in addition to neural networks span a multitude of fields, including computer vision, NLP, and recommender systems. By leveraging their data-processing power, these technologies have introduced transformative changes that drive innovation and enable new insights across diverse domains.

5.3 *Decision making archetypes and structure*

Decision-making archetypes and structures are essential across diverse fields, including healthcare, transportation, and energy. In healthcare, for example, Liu et al. [80] utilized CNNs to support the assessment and diagnosis of pressure ulcers, providing valuable insights that strengthen medical diagnostic processes. Furthermore, integrating pattern recognition tools like PANN significantly augments the precision and effectiveness of medicinal decision-making [81]. In transportation, substantial advancements in intelligent decision-making have facilitated improvements in automated vehicle safety and efficiency. Cheng et al. [82] applied CNNs to enable data-driven decision-making in autonomous systems, promoting safer and more effective transport solutions. Additionally, Li et al. [83] Utilized deep learning to automate decision-making processes in highway pavement maintenance, improving infrastructure management and ensuring greater reliability. In the field of energy, El Bourakadi et al. [84] designed intelligent energy management systems for microgrids by combining LSTM-based deep learning models with fuzzy decision-making techniques to optimize energy distribution and enhance the effectiveness of microgrid operations. Decision-making frameworks also extend to broader applications across various sectors. For instance, Costache et al. [85] combined deep learning and fuzzy logic, in addition to MCDM investigation to address flash flood risks. Using the H_2O R package, this integrated approach provides accurate predictions and supports effective flood management. Furthermore, Vo et al. [86] expanded deep learning applications to include socially responsible investing and portfolio optimization, equipping decision-makers with tools to make impactful and socially conscious investment choices. Decision-making models and frameworks are applied across multiple fields, such as healthcare, transportation, and energy. The combination of deep learning, CNNs, fuzzy logic, as well as MCDM investigation enhances decision-making precision and intelligence, improving efficiency and effectiveness across these varied domains.

5.4 *Improved precision and functioning in decision making*

Deep learning has emerged as a transformative tool, significantly enhancing decision-making processes by improving both accuracy and efficiency. Various deep learning techniques have been successfully applied across multiple domains to support intelligent, data-driven decision-making. In medical diagnostics, convolutional neural networks (CNNs) have proven highly effective in delivering precise assessments, aiding critical decision making in medical treatment [80]. Incorporation of CNNs with fuzzy logic further enhances analytical reliability, enabling more cognizant decision-making in complex healthcare scenarios [87]. In autonomous transportation, CNNs play a crucial role in processing real-time sensor data, facilitating intelligent decision-making to ensure both protection besides operational efficiency [82].

Similarly, in the energy sector, intelligent energy management systems utilize long short-term memory (LSTM) models alongside fuzzy decision-making approaches to optimize energy distribution, improving overall efficiency and sustainability [84]. Deep learning techniques also contribute to disaster risk assessment, particularly in flash-flood hazard prediction. The combination of the H_2O R package with fuzzy multi-criteria decision-making (MCDM) analysis supports accurate risk assessment, aiding proactive disaster management strategies [85]. In the financial sector, deep learning enhances socially answerable investing and assortment optimality, helping align investment strategies with ethical and sustainability principles [86]. Meanwhile, in highway infrastructure management, deep learning-based automated decision-making systems improve maintenance prioritization and scheduling, streamlining operations and enhancing long-term decision effectiveness [83]. Overall, deep learning has greatly expanded decision-making capabilities, techniques like CNNs, fuzzy logic, and LSTM models offer decision-makers valuable insights, supporting informed choices and positive results across multiple fields.

6. Adoption of AI in decision making

Researchers agree that AI can be effectively employed to collect, interpret, evaluate, in addition to propagate information, enhancing the speed, volume, diversity, and availability of data [88–90]. Acharya et al. [90] further highlight AI's potential for improving data quality, noting that excessive, insufficient, or inaccurate information can negatively impact decision-making-an issue often encountered in large, complex organizations. However, Metcalf et al. [91] underscore the challenges associated with training AI due to the ever evolving and complex nature of data. They argue that human involvement is critical to maintain data quality and interpretative accuracy, a position backed through various scholars [88, 89, 92, 93]. Furthermore, implied evidence has been identified as more influential than factual analysis in the context of strategic decision-making [91, 92]. As a result, "while humans have access to both explicit and tacit knowledge, AI is limited by its lack of access to tacit knowledge and its reliance on historical data from which patterns are identified" [91]. Some researchers suggest that group discussions can help incorporate elements of tacit understanding into decision-making [88, 89, 91]. Terziyan et al. [92] propose the most comprehensive approach for incorporating diverse types of information into decision-making, their patented Pi-Mind methodology seeks to replicate human decision-makers by capturing soft facts and potential utility levels. However, the effectiveness of the model depends on the quality of input data provided by humans. Acharya et al. propose an inter-organizational knowledge-sharing model to mitigate the associated risks of "overemphasizing technology, which could lead organizations to prioritize knowledge storage over knowledge flow". Since information volume affects all stages of decision-making, these researchers further advise allocating resources to support efficient knowledge management within organizations [90].

There is widespread agreement that AI substantially enhances the efficiency and speed of information gathering and interpretation. However, researchers argue that high-quality outcomes still depend on human expertise and the willingness to share implicit knowledge. Many studies recommend a hybrid approach, pointing out that while mathematical models alone may struggle to manage large datasets, these datasets are crucial for training machine learning uses, which frequently rely upon proceeding such models [94, 95]. This backs Simon's [96] claim that AI systems extend beyond pure mathematical frameworks. The literature outlines several practical and hypothetical applications of AI, particularly in data interpretation, generating alternatives, and establishing probabilities and preferences, which may also include assessing potential consequences [94, 97, 98]. AI is anticipated to fully automate information collection by leveraging natural language processing, text mining, and various data-mining techniques to integrate data from multiple sources [94, 95]. Nevertheless, human input remains essential, especially in feature engineering, to counteract input biases, with top-down applications providing necessary guidance [99]. We believe that the role of AI in organizational decision-making is still a topic of debate. In their literature review, Baryannis et al. [94] note that most studies do not attribute complete decision-making capabilities to AI; some recommend employing bottom-up approaches as decision-support systems. Empirical studies in the literature primarily explore AI's role in gathering information and monitoring status within production and logistics, utilizing tools like the data science toolbox by Flath et al. [99], supply chain risk management tools by Baryannis et al. [94, 97], and the self-adaptive supply chain projected by Calatayud et al. [100]. Conversely, Colombo [101] portrays a notable exception with holistic risk analysis and modeling (HoRAM), a validated approach that supports nearly the entire decision-making process in dynamic environments.

6.1 *Impact on organizational structure*

Von Krogh [102] draws on Herbert Simon's insights, stressing the close relationship between organizational structures and the decision-making processes due to human cognitive limitations. He suggests that to address these constraints, "decision-making authority and information processing can be distributed across various roles and units with differing interdependencies". Organizational strategies and goals play a critical role in defining these roles and relationships, promoting effective information management, and influencing each phase of strategic decision-making [102]. Additionally, these strategies and objectives are fundamental drivers in the adoption of AI [102–105]. They form the basis for reshaping or establishing new organizational frameworks necessary for smooth AI integration [102, 105, 106]. Furthermore, von Krogh [102] highlights that as AI is implemented, it alters organizational structures, impacting processes and redistributing responsibilities. Bienhaus et al. [103] and Butner et al. [104], drawing from survey data, advocate for a complete process redesign instead of merely adding new technologies onto existing frameworks. Paschen et al. [105] support this transition by offering a four-dimensional framework to assess if AI adoption fosters novelty in produces or else progressions and whether it enhances or reduces human competencies. Through the interaction of these dimensions, organizations can achieve "various value-creating innovations" [105]. Lismont et al. [107] present another perspective, classifying organizations by their readiness for technology adoption. Their findings suggest that as companies become more advanced in AI usage, they diversify the range of applications, affected processes, and associated goals. Given these interdependencies, Tabesh et al. [108] advocate for incremental changes to organizational structures, ensuring alignment with the overarching strategy. In our opinion, organizational structures are foundational to the effective integration of AI, while the adoption of AI, in turn, reshapes these structures. The strategic drivers behind AI implementation dictate its form and deployment, while the available AI applications necessitate adaptations to existing decision-making processes to fully realize AI's potential.

6.2 *Challenges in strategic decision making*

AI literacy is recognized as a key factor influencing the decision to incorporate AI to present business operations, as well as determining the methods and purposes for doing so [109–111]. AI literacy includes the knowledge of machine learning models and deep learning architectures. As Migliore et al. [112] point out, "Not every decisionmaking challenge requires a technological solution". AI literacy broadly encompasses a comprehensive understanding of AI's strengths and limitations-a competency often lacking in organizations, as Whittle et al. [113] observe. To enhance AI literacy, researchers emphasize involving both top management and impacted employees in AI initiatives, given that acceptance varies across organizational levels [111, 114]. Stakeholders are encouraged to take ownership by becoming familiar with AI and actively participating in its integration, helping them to define their roles. Therefore, education and training are crucial for successful AI adoption [111, 115]. Scholars including Migliore et al. [112], Bader et al. [109], and Whittle et al. [113] advise assessing the skills employees need to work effectively with AI, with leadership providing guidance during this transition based on their AI expertise [111, 113, 115].

Moreover, soft skills like collaboration, creativity, and sound judgment are expected to play a larger role as AI becomes integrated into decision-making [111]. A gradual approach to AI implementation is recommended [111, 115], as trust in the technology grows through increased use and familiarity, enabling employees to adapt to AI-assisted tasks [110, 111]. Transparency-defined as clear information about data nature, flow, and processing contexts [116] is also essential for successful AI adoption [109]. Diverse teams comprising both new and experienced organizational leaders, as well as those with adequate training, are suggested for introducing AI [110, 111, 115]. Leadership is responsible for choosing the right team and supporting the integration process, with Kolbjørnsrud et al. [111] noting that senior leaders are more attuned to this responsibility than middle managers. Concerns around data security, privacy, and potential data manipulation are addressed by numerous authors, who stress the importance of assessing these risks before deploying new technologies [109–111, 113, 116, 117]. While transparency and AI literacy are expected to mitigate bias, some researchers suggest that increasing data availability may also help. Migliore et al. [112] discuss bias as stemming from bounded rationality, a concept distinct from this study's definition (see Introduction), raising the question of whether more data always improves outcomes. Additionally, acquiring the right quality and quantity of data remains a challenge [109, 110, 118]. Bellamy et al. [118] argue that "machine learning is always full of statistical discrimination", implying that AI systems inherently carry bias. To address this, frameworks such as AI Impartiality 360 [118] as well as Open Algorithm [110] offer preprocessing, inprocessing, as well as post-processing techniques aimed at reducing bias, though not eliminating it entirely. Canhoto et al. [109] further emphasize that decision quality is influenced by the specific AI application used, available resources, the quality of input data, and human interpretative skills.

In our view, the literature highlights that education, training, and attention to data security are essential to promoting AI literacy and transparency, helping to reduce potential risks. Additionally, the gradual introduction of AI and active employee engagement are crucial for effective implementation. While it may be challenging to eliminate bias, whether implicit or explicit, these actions can enhance awareness of such concerns. Nonetheless, several authors emphasize the need to integrate ethical and moral considerations throughout AI's procedural and structural deployment.

6.3 *AI's impact on task division in strategic decisions*

Research suggests that combining the distinct potencies of beings along with AI be able to produce a synergistic effect, enhancing effectiveness in addition to its viability in decision-making processes [119–122]. Numerous studies highlight the complementary relationship between humans and AI, where AI systems improve through human input and humans gain insights from AI support [119, 123]. This perspective is reinforced across disciplines, with contributions from Kolbjørnsrud et al. [111], Terziyan et al. [92], von Krogh [102], and Blasch et al. [95], underscoring the topic's relevance. Various frameworks have been proposed to allocate tasks between humans and AI, spanning from fully automated AI solutions to hybrid models and human-exclusive decisions [121, 124]. However, Parry et al. [125] and Agrawal et al. [126] consider complete AI autonomy viable for certain decisions, they also stress that for high-stakes decisions, human oversight or "veto power" is essential [125, 127], highlight AI's ability to "automate tasks", allowing humans to focus on higher-value work, while Klumpp et al. [128] advise that AI shifts human roles toward supervisory responsibilities rather than direct task execution. By automating certain decision-making tasks, AI enables individuals to concentrate on areas where AI is less capable, but which are critical to strategic decision-making. Researchers emphasize that humans are more adept in areas such as judgment, political analysis, psychological insight, Agility, imagination, strategic foresight, along with managing ambiguity [119, 121, 122, 125, 126, 129]. Even when machines can identify optimal decisions, they may struggle to effectively communicate and gain support from diverse stakeholders [119]. In our assessment, the literature suggests that while AI has the potential to augment human capabilities, it reshapes the human role to focus on supervision. The authors suggest that AI will play a limited part in strategic decision-making within organizations, with key human skills still being indispensable. Lyons et al. [130] further argue that, for human-AI cooperation to be effective, all involved parties must clearly identify their tasks, errands, along with onus, with an elevated degree of transparency necessary, akin to the dynamics in human-only teams.

6.4 *AI integration in decision-making under uncertainty*

Most scholars argue that strategic decision-making within organizations is fundamentally human led, with technology acting as a supportive component. However, there is widespread agreement that AI and human skills can work synergistically. Addressing the initial sub dimension of the research question, the intangible outline considers how tasks may be distributed between human decision-maker as well as AI, identifying knowledge management as a key area requiring in-depth analysis. Researchers commonly acknowledge that AI can gather large volumes of evidence regarding varied resources, streamline data allocation, in addition to it assist in construal, enhancing knowledge management in terms of efficiency and speed [88, 90, 95, 104]. Nonetheless, AI faces limitations when it comes to accessing implicit knowledge that stakeholders may be unable or unwilling to share. While initial methods to address this challenge have been introduced, more work is needed [91, 92, 101], researchers contend that the quality of implicit knowledge continues to rely on human input and must be framed and evaluated through human interaction [131]. The task allocation framework consolidates current academic discussions regarding the specific tasks AI is most suited to support. The success of AI integration is highly dependent on the application, and vice versa. While human judgment is still considered essential for utility assessments [98], AI can assist by forecasting the potential impact of various decision alternatives on the organization and its stakeholders [94, 101, 126]. This capability can influence how alternatives are evaluated, with AI performing the mathematical calculations involved. However, final decisions remain the responsibility of human decision-makers. At present, AI contributes most significantly to the input and processing stages, particularly within knowledge management [89, 95, 102, 132]. However, numerous AI applications in use today fall short of meeting Nilsson's [133] criteria for intelligence. The selection of AI applications is influenced by an organization's structure and resource allocation, although studies indicate that AI can, in turn, impact organizational design and structure [107, 108]. Scholars further indicate that organizational structure serves both as a prerequisite for and a consequence of AI integration in decision-making beneath indecision [102, 105, 108]. For successful AI implementation, a well-defined organizational strategy and a clear rationale for integrating AI into decision-making processes-particularly in areas among them knowledge management-are critical [102–104].

Data transparency and AI literacy are essential foundations for effectively integrating AI systems, as emphasized in numerous foundational frameworks. Scholars argue that equipping employees with the necessary skills to effectively utilize AI is vital [109, 110]. Employees must be knowledgeable about which AI applications are appropriate for specific tasks, the types of data required for accurate performance, and how to interpret AIgenerated outcomes. Moreover, research demonstrates that continuous training and hands-on experience with AI foster trust in the technology, thereby enhancing its overall efficacy [110, 111]. The issue of moral responsibility in AI decision-making remains unresolved, as it is currently impossible to embed comprehensive moral principles into algorithms [134, 135]. Studies highlight those machines cannot be held morally accountable, underscoring the necessity of adapting ethical constructs, such as guilt and fairness, to AI contexts [136]. However, there is no established method for integrating these ethical considerations into AI systems. The analysis suggests that incorporating AI into directorial decision-making beneath conditions of uncertainty is influenced by numerous factors, complicating the development of clear guidelines. Researchers emphasize that AI requires well-defined objectives, as it struggles with managing uncertainty and processing complex inputs [102, 119, 122]. Nilsson [133] notes that AI can only "interact with foresight in its environment" when directed by human input, a view contrasting with Simon's [96] comparison of AI and human capabilities. Some scholars advocate for advancing AI into more so- phisticated, self-learning systems with greater intelligence [115, 125, 126, 137]. However, there is no consensus on whether AI will ever fully replicate human implicit abilities [121, 136]. Furthermore, AI cannot fully replace the advantages of human group decision-making and may, in certain instances, intensify the complexities involved in being decision-making processes [99, 117]. Concerning personal decision-making, AI's effectiveness is often limited, as vital soft skills and the varied experiences that support well-rounded decisions are best achieved through human interaction and discussion. As Rousseau [131] points out, "recognizing biases in others is often easier than seeing them in ourselves". In our view, the use of AI in organizational decision-making represents a shift in the role of human decision-makers, who are now evolving into supervisors of AI systems [127, 128]. This supervisory role differs from traditional production processes, requiring a deep understanding of AI's functionalities and the ability to accurately interpret and translate its outputs. Effective and responsible supervision of AI systems demands a comprehensive grasp of both the technology's limitations and its potential [109, 113, 130].

7. Conclusions

The decision-making landscape is profoundly transforming as advanced computational techniques like optimization algorithms, neural networks, and artificial intelligence (AI) become increasingly integrated into decision processes. This review has explored this evolving landscape, examining the theoretical foundations of decision-making, the application of sophisticated tools, and the challenges and opportunities presented by human-AI collaboration. The review highlights the limitations of traditional normative decision-making models in capturing the nuances of human behavior. While offering a more realistic perspective, descriptive theories often grapple with the complexities of cognitive biases and heuristics. This necessitates a nuanced understanding of both perspectives to guide decisionmaking effectively. Integrating neural networks and deep learning introduces powerful tools for analyzing complex data patterns and enhancing prediction, classification, and decision-making. The review explored various neural network architectures, each with its unique capabilities and limitations, demonstrating the potential of these technologies for a wide range of applications. The impact of AI on organizational structures and decision-making processes is profound. While AI excels in data analysis and pattern recognition, human judgment remains indis-pensable for strategic decisions, particularly those involving implicit knowledge, ethical considerations, and the management of uncertainties. The review emphasizes the importance of fostering AI literacy and transparency, ensuring that AI integration maximizes benefits while mitigating risks. Ultimately, the future of decision-making lies in the synergistic partnership between human and AI capabilities. AI can effectively augment human decisionmaking by automating tasks, providing insights from vast datasets, and facilitating data-driven analysis. However, human oversight and judgment remain critical for strategic decisions, particularly those with significant ethical implications, complex uncertainties, and the need to navigate human social dynamics. This review underscores the need for a multi-faceted approach to decision-making, integrating theoretical frameworks, advanced technologies, and thoughtful considerations of human and AI capabilities' unique roles and limitations. As AI continues to evolve, ensuring a responsible and collaborative relationship between humans and machines will be crucial for navigating the complexities of decision-making in a dynamic and uncertain world.

Data availability statement

No data was used for the research described in the article.

Conflict of interest

The authors declare no conflict of interest.

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