**MEHREGAN ESKANDARIVATANNEZHAD**
SUPERVISOR: ROBERT KREUZBAUER

# Human-AI symbiosis: The best approach for AI implementation in business decision-making in complex systems

**Master thesis, 2023**
**Master of Science in Business Administration**
**University of Stavanger Business School**
**Specialization: Leadership in Digital Economy**

## Abstract

In today's business landscape, there is significant discourse surrounding the role of Artificial Intelligence (AI) in various aspects of business operations. Decision-making, in particular, is a crucial component of every business-related activity. As businesses expanded and generated massive amounts of data, it became clear that humans alone could no longer make consistently accurate decisions. Moreover, it is demonstrated that humans often rely on heuristics and cognitive biases in their decision-making, leading to suboptimal outcomes. Given today's business environment's complexity, instability, and interconnected nature, businesses possess all the characteristics of complex systems. With the aid of AI, decision-making can be significantly enhanced. Various subfields of AI, such as artificial neural networks, fuzzy logic networks, and agents, have been developed in recent years, playing a pivotal role in enabling AI-driven decision-making.

Findings through using purposeful and complex systems suggest that although AI subfields in decision-making can make sound decisions, they exhibit deficiencies in complex systems where human interaction and interconnectedness across different organizational levels are present. Currently, AI technology is not equipped to address these challenges. As a result, the decision-making process should not be entirely delegated to machines and AI. This discussion gives rise to the duality of augmentation and automation. Decision-making can be categorized into three levels: operational, tactical, and strategic, ranging from structured to unstructured decisions. The analysis reveals that AI performs admirably as an assistant or replacement tool at the operational level. However, as moving towards tactical and strategic decisions, although its augmentation abilities remain somewhat consistent, its capabilities for replacement and automation diminish significantly. Consequently, AI is believed to lack the ability to automate strategic and unstructured business decisions completely.

## Preface and Acknowledgment

As a student of the Business School at the University of Stavanger, it is with great enthusiasm and dedication that I present this preface for my master's thesis.

The complexity of today's business environments has reached unprecedented levels, driven by factors such as globalization, interconnectedness, and the rapid advancement of technology. As a result, decision-making processes within organizations have become increasingly intricate, requiring a deep understanding of complex systems and the ability to navigate through a myriad of variables and uncertainties. Within this context, the exploration of artificial intelligence as a means to enhance decision-making has gained significant attention and importance.

The title of this master thesis, "Human-AI Symbiosis: The Best Approach of AI Implementation in Business Decision-Making in Complex Systems," encapsulates the essence of the research conducted in this study. It explores the optimal integration of AI into business decision-making processes within the context of complex systems, emphasizing the symbiotic relationship between human expertise and AI capabilities.

The motivation behind selecting this topic was twofold. Firstly, witnessing the rapid expansion of technology usage in various aspects of business operations and the growing reliance on AI solutions in decision-making processes, it became imperative to examine the effectiveness and best practices of AI implementation. Secondly, the recent publicity surrounding AI, accompanied by inflated expectations and exaggerated claims, necessitated a comprehensive review of AI applications in the business field.

I would like to express my deepest gratitude to my supervisor, whose invaluable guidance, support, and expertise have been instrumental in shaping this thesis. His continuous encouragement and insightful feedback have contributed significantly to the development and refinement of this research. I would also like to extend my thanks to all the individuals who have provided their time, knowledge, and assistance throughout this journey.

It is my sincere hope that this master's thesis contributes to the existing body of knowledge on AI implementation in business decision-making, ultimately assisting organizations in harnessing the power of AI while maintaining a harmonious collaboration between humans and machines.

Mehregan Eskandari Vatan Nezhad
Stavanger
June 2023

Table of Contents

## Introduction

Approximately half a century to three-quarters of a century ago, decisions in business were mostly taken through human assessment. Decision-makers depended on their finely-honed intuitions, which were formed from an extended period of practice (as well as a small sum of data) in their specialized field.

Tversky and Kahneman (1981) explain that the foundation of resolutions and predictions regarding human choices in daily life and business often rests on the premise that individuals act rationally. It is proposed that most methods used to effect decision-making are rooted in a rational planning methodology (Glouberman & Zimmerman, 2002). The advent of connected devices and the vast amounts of data they create have necessitated adapting our systems (Colson, 2019).

The data can provide a foundation for more effective decisions; extracting suitable insights and taking the necessary actions is possible by processing this data. Businesses are increasingly adopting data-driven procedures for making decisions. While data can be advantageous in the decision-making process, it is necessary to have a fitting processor to utilize the data optimally. Generally, it is presumed that the processor is an individual, and the term “data-driven” indicates that the data must be organized and summarized to be discernible to individuals. The result is a data-driven system wherein human judgment remains at the core (Colson, 2019).

The use of technology can help to enhance human decision-making by providing support in areas such as finding and choosing relevant data, formulating a decision model based on specific circumstances, illustrating the outcomes to the individual making the decision, and aiding the decision maker in comprehending the results of the decision model (Phillips-Wren, 2012). Information systems and technology of any business play a vital role in the decision-making and business operations (Phillips-Wren et al., 2009). Digitalization permits organizations to function on an exceedingly precise level and make countless daily decisions associated with a single client, commodity, provider, asset, or exchange. Nevertheless, these decisions cannot be taken by humans working on data sets (Ross & Taylor, 2021).

To optimize the potential of data, firms must integrate artificial intelligence (AI)[1] into their operations and sometimes exclude individuals' shares. Data-driven workflows must change to AI-driven ones (Colson, 2019). In recent years, AI has witnessed considerable advancement concerning automating human cognitive capabilities (Monostori, 2003). Adopting systems incorporating AI by businesses is increasingly widespread and accelerating rapidly (Miller, 2018). AI can facilitate the decision-making process for complex problems by incorporating data transmission with analysis (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

AI is now revolutionizing the realm of business, enhancing ingenuity and efficiency. Nowadays, companies can leverage AI to enhance their decision-making (Dordevic, 2022), as AI can outperform human decision-making in terms of speed and precision (Chimera, 2023).

Nevertheless, Gordon (2021) asserts that the apparent neglect of complexity science concerning the advancement of AI elicits a sense of astonishment. Complexity science directs its attention towards transcending the confines of individual disciplines. It operates within the intricate interplay of diverse complexity science has exerted a profound and transformative influence within the domains of physical and biological sciences since the 1970s. Nonetheless, it is noteworthy that only within the last ten years has its true significance within the business realm begun to be comprehensively acknowledged and valued. An emerging trend in the field involves the convergence of AI and complexity sciences, which emphasizes the recognition of our existence within a remarkably uncertain and unforeseeable world. Gaining a comprehensive understanding of the multifaceted complexities associated with facilitating AI technologies is vital for assessing the maturity of AI within businesses. This comprehensive comprehension can improve business outcomes.

The term "complexity" holds significant prominence in business but remains elusive due to its inherent ambiguity. Complexity is the existence of a multitude of diverse elements (e.g., specialized technologies, natural resources, artifacts, people, and departments) interconnected through numerous relationships. Both the abundance of elements and the

---

[1] In this thesis, the term 'AI' refers to a broad range of technologies and systems that exhibit intelligent behavior in business decision-making. For the purpose of this study, the following terms, including but not limited to, Expert Systems, Intelligent Decision Systems, and Knowledge-Based Decision Support Systems, will be considered as subsets of AI. So, the term AI might be used instead to cover the general objective, except for the situations where the exact meaning is meant. These terms encompass various approaches and methodologies that utilize computational techniques to simulate human expertise, automate decision-making processes, and provide intelligent insights and recommendations for business applications.

intricate connections among them can serve as sources of advantage or disadvantage, contingent upon the effectiveness of their management (Reeves et al., 2020).

Mowles (2014) claims that today's businesses are characterized by their Increasing complexity. This complexity is further compounded by the dynamic nature of the environment and the uncertainty it brings (Monostori, 2003). Multiple demands for using complexity sciences in the past decade are partially due to the expanded vision of many social advancement plans structured with multiple aims and developments (Mowles, 2014) and the recognized lack of effectiveness of linear strategies (Monostori, 2003). It has been argued that traditional decision-making models should be reassessed due to our augmented comprehension of continuously evolving, highly unpredictable contexts (Glouberman & Zimmerman, 2002).

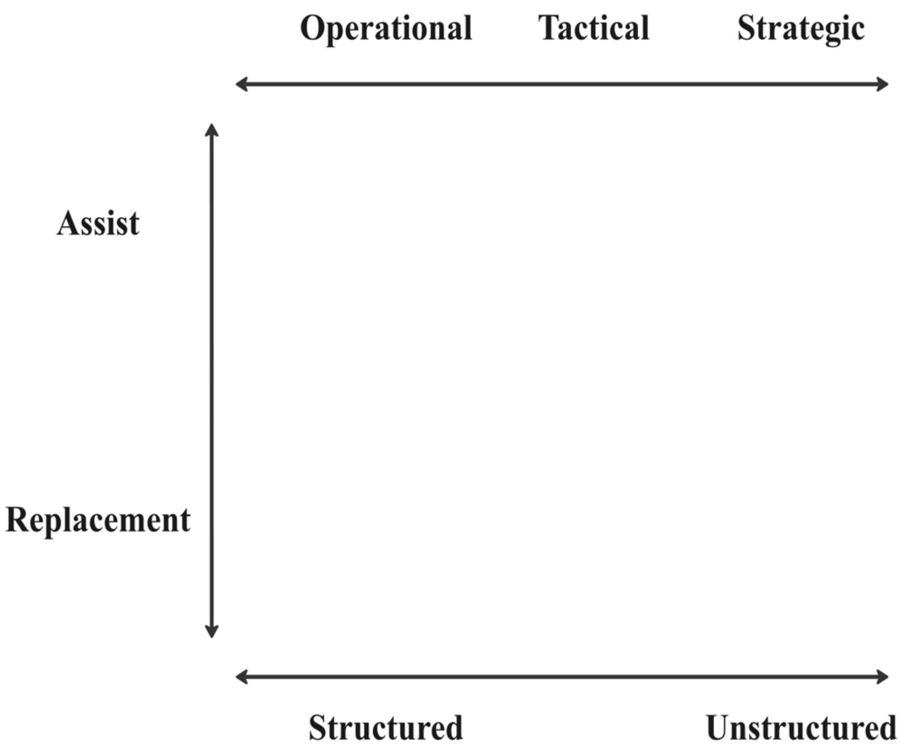
It can be tempting to envision the processes proceeding in a methodical and systematic progression, like AI will be implemented, and all problems will be solved instantly, yet this is not the case. Unexpected impediments arise, and unforeseen events happen, necessitating a shift in either approach or procedure as dictated by environmental feedback (Taylor, 1978, as cited in Glouberman & Zimmerman, 2002). The potential impact of decisions made in one area will likely echo across multiple sectors. Attempting to produce the preferred results directly will likely impact other levels of complexity existing in the complex web of interconnected components (Cabrera & Cabrera, 2019). The premises behind rational decision-making are incompatible with complex systems; thus, strategies and initiatives based on this idea can bring about unexpected results when utilized in complex systems**.** When interfering in complex systems like AI and decision-making integration, in-depth consideration must be taken. However, the planning needed is distinct from that of mechanical approaches. Local circumstances must be taken into account, and one must bear in mind the unpredictability and feedback that may arise from any interference (Glouberman & Zimmerman, 2002).

Decisions can be classified into three sections: operational, tactical, and strategic (Edwards et al., 2000) or a range from structured to unstructured (Turban & Aronson, 1998). Some decisions (Strategic/unstructured) are rare choices that have a crucial impact on the progress and continuation of an organization, and they are made by head executives (Berthet, 2022). Such decisions involve imprecise, complex, and unpredictable issues and problems, making them more challenging to resolve (Hodgkinson, 2001, as cited in Berthet, 2022). On the other hand, (McAfee & Brynjolfsson, 2017) brought up a fundamental concern: whether AI is fully capable of tackling business problems and making the right decisions in today's business world according to its unstable, complex, and dynamic context.

The complex and dynamic issue lies in incorporating AI-powered automation or augmentation alongside individuals in organizations and social structures (Miller, 2018). The contrasting perspectives of prominent scholars necessitate a deeper examination of the potential for human-AI coexistence and strategies to mitigate the adverse consequences of this technology (Duan et al., 2019). Thus, in addition to discussing different levels of decision-making in businesses, the automation and augmentation duality in human-AI decision-making will be evaluated in this study, and it will be assessed that either automation or augmentation is suitable for each specific level. So, the objective will be to find the approximate covered space of the following diagram.

**Figure 1**

*AI implementation in different decision-making levels framework-Unfilled version*




*Note.* An unfilled framework of the range of businesses' decision-making and problem levels (operational, tactical, and strategic) and the corresponding possibility of implementing assistant or replacement AI. In Figure 4, p. 46 completed version is illustrated

Consequently, businesses must acknowledge the significance of complexity science and system thinking disciplines. By doing so, they can enhance their understanding and recognition of AI while also facilitating the adaptation of our world to the presence of AI technologies. Sustained business progress necessitates constant leadership efforts to instigate change and assess the specific domains and complexities at which AI should be employed to bolster business objectives and foster expansion (Gordon, 2021).

## Methodology

This study explores the best approach for implementing AI in businesses' decision-making processes in complex systems. Given the non-empirical nature of this research, the methodology employed in this study involves a comprehensive literature review and analysis of existing academic research, industry reports, and expert opinions. The reason for adopting a non-empirical approach is either not considerable companies have implemented such an approach or the unavailability of specific data related to the implementation of AI in businesses' decision-making processes, as such data is considered confidential by the companies involved.

**Literature Review:** The methodology begins with an extensive literature review in each section, which involves collecting and analyzing relevant academic articles, books, research papers, and industry reports. The review focuses on the current state of AI implementation in decision-making processes, with particular attention to complex systems within businesses. It also explores the concepts of human-AI symbiosis, augmentation, and automation in decision-making, in addition to the different capabilities of the AI subfields.

**Identification of Key Concepts:** Based on the literature review, key concepts and theoretical frameworks related to AI implementation in decision-making processes are identified. These concepts include complex systems theory, decision-making heuristics, AI capabilities and subfields, decision-making levels (operational, tactical, and strategic), and the capabilities and limitations of AI in addressing complex system challenges.

**Data Collection:** While the study does not involve primary data collection, relevant secondary data sources are collected and analyzed. These sources include scientific articles, industry reports, case studies, and expert opinions from professionals working in the field of AI implementation. This data provides insights into real-world applications and challenges businesses face implementing AI in decision-making processes.

**Framework Development:** Based on the literature review and findings, a conceptual framework is developed to guide the best approach for AI implementation in businesses' decision-making processes. This framework considers the different decision-making levels, the nature of decisions (structured vs. unstructured), and the role of human-AI symbiosis in achieving optimal outcomes.

**Validation:** The developed framework is reviewed and validated by experts in AI implementation and complex systems. Their feedback and insights contribute to the refinement of the framework, ensuring its robustness and applicability to real-world business scenarios.

**Discussion and Conclusion:** The study concludes by summarizing the key findings from the literature review and framework development. The implications and recommendations for businesses seeking to implement AI in their decision-making processes within complex systems are also discussed.

## Complexity

Humankind's thinking, comprehension, and behavior can indeed be identified as being complex (Cabrera & Cabrera, 2019). Complexity theory attempts to comprehend how structure and constancy are generated by collaborating several elements based on simplicity. Additionally, there is an awareness of human structure regulations' complexity, nonlinearity, multidimensionality, and interconnectivity (Kuhn, 2008; Mason, 2008, p. 1, as cited in Cabrera & Cabrera, 2019). It is widely accepted that knowledge from the complexity sciences offers valuable perspectives on why social behavior is uncertain (Mowles, 2014).

If complexity is known as the condition of being complex, then what precisely is "complex"? Dictionary entries may refer to interrelated components or intricate arrangements. However, recognizing the difference between complicated and complex is crucial (Cabrera & Cabrera, 2019). Some scholars have proposed that the complexity sciences may exclusively be helpful in certain situations and times, depending on the analyzer's evaluation. The authors maintain that programs can be divided into three categories: simple, complicated, or complex, with the potential for complex programs comprising simple and complicated components. Adopting a complexity standpoint is another valuable asset for a logical analyst in an area loaded with countless methods, approaches, and hypotheses, all equipped with conditional (if, then) reasoning (Mowles, 2014).

### Simple, complicated, complex

Usually, the words 'complicated' and 'complex' are considered synonyms and used to define the exact attributes. However, for the purpose of this study, it is crucial to define their distinctions clearly.

Glouberman and Zimmerman (2002) explain that simple issues like reading the instructions may include some fundamental language and methodology challenges, but when these have been acquired, following the formula provides a high degree of assurance of success.

An example of a simple problem in business scope can be calculating the total monthly sales revenue by adding up individual sales figures. This problem involves basic arithmetic and can be easily solved by simple calculations.

Complicated issues involve elements that are made up of simple issues. Still, they cannot be downsized to just these. Their complicated character is often not merely associated with the size of a problem but also with collaboration or technical knowledge. Despite being able to be generalized, complicated issues are not just a combination of simple elements. An example of a complicated problem in business scope is implementing a new enterprise resource planning (ERP) system across a multinational organization. This problem requires integrating multiple departments and procedures, ensuring data consistency, and training employees on the new system.

Complex issues can include both simple and complicated issues, yet they cannot be simplified into either. Such problems have special needs that must be taken into consideration, such as comprehending regional circumstances that are distinct, interdependency, the additional quality of non-linearity (Glouberman & Zimmerman, 2002), as well as the capability to accommodate as circumstances evolve (Kauffman, 1995). Complicated systems inevitably involve considerable obscurity, unpredictability, and insecurity (Glouberman & Zimmerman, 2002). An example of a complex problem in business scope is developing a comprehensive business strategy for entering a new global market. This problem involves analyzing market dynamics, understanding cultural nuances, assessing regulatory environments, conducting extensive market research, identifying local partners, and adapting the business model to meet unique customer needs. It requires continuous monitoring, strategic flexibility, and adaptive decision-making to navigate the complexities and uncertainties of entering a new market.

A widespread misinterpretation of the origin of complexity causes frequent misbelief concerning the correlation between complex and complicated. Complexity is not generated by complicated subsystems which blend to create complex systems. Complex matters result from simple instructions (Cabrera & Cabrera, 2019). This concept may seem paradoxical to some, but as (Gell-Mann, 2002) clarified, the complex nature of the universe reveals the linkages between the basic fundamental laws which control the behavior of all matter in the cosmos and the complex web observed today, characterized by diversity, singularity, and evolution. What separates the complex from the complicated is their capacity to alter and modify to enhance fittingness to environmental circumstances (Cabrera & Cabrera, 2019).

Complex problems are often referred to as "wicked" issues because a vast number of their features cannot be broken down into their essential elements. Once these issues are resolved, the solutions do not serve as formulas that can be implemented for other similar issues. Frequently, these issues present difficulties in prediction. (Kauffman, 1995). Generally, the complexity observed at the system level can be ascribed to the associations between the components of the overall entity (Cabrera & Cabrera, 2019).

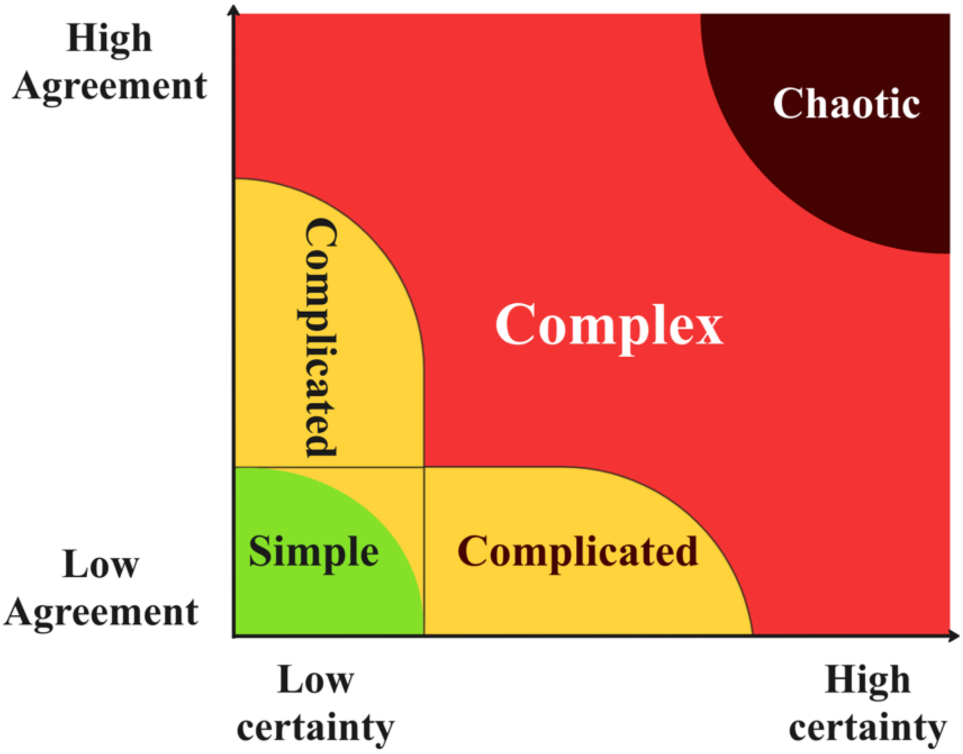
**Complex Adaptive Systems (CAS)**

Business contexts can be considered complex adaptive systems (CAS) due to the dynamic nature of the modification that occurs when autonomous agents' collective behavior and interconnection come into play (Cabrera & Cabrera, 2019). Several scholars have proposed the concept of CAS. This system comprises numerous agents that adhere to procedures and regulations. Each agent collaborates with other agents and adapts accordingly. The result is a system that shapes a population-wide model. An example of a CAS is a flock of birds where thousands of independent actions in accordance with non-complex directives adapt to their neighbors' motions, ultimately creating a population-wide scheme of "flocking" (Stacey, 2011). A CAS can be an essential component of another CAS, potentially including a minor CAS. Furthermore, CAS can generate new CAS over time (Gell-Mann, 2002).

Scholars researching complexity sciences need to clarify their topic for themselves and their readers, leading to their usage of the Stacey matrix. Stacey's matrix presents an understanding of organizations as CAS, suggesting that the type of decisions leaders must make will be determined by the circumstances they are confronting. In scenarios of high unpredictability and conflict, Stacey contends that the traditional linear/rational approaches of evaluation and decision-making are ineffective (Mowles, 2014).

**Figure 2**

*Stacey matrix*




*Note:* Adapted and modified from "A Board's Journey into Complexity Science: Lessons from (and for) Staff and Board Members", by Zimmerman and Hayday, 1999, *Group Decision and Negotiation*, *8*(4), 281–303. https://doi.org/10.1023/A:1008709903070. Copyright 1999 by Kluwer Academic Publishers. Adapted with permission.

Morrison (2002, as cited in Cabrera & Cabrera, 2019) posits that complexity is the foundation for any organization and business, whether it is of a biological or social nature, that enables it to endure, evolve, expand, and adjust. Administrators in all disciplines should adopt the science of complexity to achieve structure and content, synchronization of short- and long-term goals, and capacity to adjust (Gell-Mann, 1995). Waldrop (1992, as cited in Cabrera & Cabrera, 2019) outlined Gell-Mann's distinctive manner of thinking, revealing that statements were not restricted by linearity and gradual advancement to demonstrate that complexity science impacts the same way science is conducted in general. Despite traditional linear models, recent research into complex systems has revealed that cumulative or small-scale inputs may have immense or extreme effects (Glouberman & Zimmerman, 2002).

## Decision-Making

Having an evolutionary perspective on human decision-making, Gibbons (2007, as cited in Hjeij & Vilks, 2023) links the evolution of the human brain to the discovery of fire, which decreased energy requirements for digestion and allowed for brain growth. Developing a larger brain facilitated improved communication and cooperation, giving Homo sapiens an advantage over other primates.

The exact origin and development of conscious decision-making in the human brain remain uncertain. Nevertheless, it is widely acknowledged that humans utilize a distinct type of decision-making that is characterized by gradual, commanded, and conscious processes in addition to the rapid, instinctive, and typically non-conscious type of decision-making that is equivalent to animal behavior (Hjeij & Vilks, 2023). Decision-making is an innately human action that can substantially impact (Phillips-Wren, 2012).

### Bounded Rationality

Unlike the common belief, human evolved decision-making and is not completely functioning on the levels of rationality. The concept of "bounded rationality" originated from the study of organizations (Berthet, 2022). Simon's influential paper in the mid-1950s on "A Behavioral Model of Rational Choice" emphasized the concept of bounded rationality, which suggests that individuals face limitations in terms of time, cognitive resources, and data when making decisions (Simon, 1955; Hjeij & Vilks, 2023).

The conventional view of business decision-making assumes that people act rationally, optimizing their choices based on all available information. However, Herbert Simon challenged this view and proposed the concept of "satisficing," which combines "satisfy" and "suffice." In the 1940s, researchers observed that people often fail to meet the two requirements of rational decision-making: (a) having complete and perfect information and (b) evaluating every possible choice prior to decision-making. This behavior is strongly linked to the escalating expense and difficulty of gathering data. People instead decide based on incomplete information and settle for the first satisfactory choice. Simon argued that this satisficing approach accurately represents how humans make decisions. He concluded that the human brain has a limited capacity to process information during decision-making procedures (Barros, 2010; Byron, 1998, as cited in Hjeij & Vilks, 2023; Hjeij & Vilks, 2023). Numerous decisions are made based on assumptions regarding the probability of uncertain occurrences (Tversky & Kahneman, 1974). One of the tools developed by humans regarding discussed attributes is their heuristics.

**Heuristics**

The meaning of heuristics underwent significant changes in the late 1960s and early 1970s, to the extent that it was almost reversed (Ahmad & Shah, 2022). The concept of heuristics has gained substantial attention in various fields over the last five decades. These cognitive strategies have been studied in various disciplines, such as business, psychology, economics, and computer science (Hjeij & Vilks, 2023).

According to evolutionary psychology, human behavior has developed over time to enhance survival in the face of environmental challenges (Buss and Kenrick, 1998, as cited in Hjeij & Vilks, 2023). individuals utilize a restricted set of heuristics when confronted with the challenging assignment of evaluating probability. This methodology simplifies the complicated task of evaluating probabilities and forecasting values into more manageable cognitive operations (Tversky & Kahneman, 1982).

Heuristics do differ from some other, often more complicated processes in one specific way: Heuristics are approaches to problem-solving that do not provide the best outcome. The utilization of heuristics may necessitate instinct, speculating, investigation, or expertise; specific heuristics can be intricate while others serve as mere shortcuts; some may be articulated in vague or imprecise terms while others are precise algorithms (Hjeij & Vilks, 2023).

The use of heuristics, or mental shortcuts, is a widely recognized phenomenon when individuals consider risks, as these strategies aim to streamline their thought processes (Kahneman et al., 2017). Typically, these heuristics are advantageous (Tversky & Kahneman, 1974). However, this practice can lead to systematic mistakes, which are referred to as cognitive biases (Berthet, 2022).

Based on cognitive theory, it is believed that cognitive biases and heuristics can lead people to make irrational decisions. Cognitive biases are individual convictions that assist people in coping with challenging judgments (Ahmad & Shah, 2022).

Ahmad and Shah (2022) add that in some cases, Heuristics are procedures used in studies of logic and decision-making that prevent individuals from coming up with the right answers to issues posed by the probability theory. Within this line of research, investigations mainly focus on the general principles of heuristics, which tend to differ from rational estimations, resulting in what is known as behavioral biases. As a result, heuristics have been linked with irrationality and inevitable cognitive delusions.

Shah and Oppenheimer (2008, as cited in Ahmad & Shah, 2022) propose that all heuristics involve lowering cognitive effort by utilizing one or more of the following methods:

analyzing only a limited number of signals, simplifying the process of retrieving signals, integrating a smaller amount of data, or analyzing only a small number of options. Therefore, heuristics are commonly known as "rules of thumb" or cognitive shortcuts that individuals utilize in intricate and ambiguous circumstances to facilitate efficient and straightforward decision-making. Business professionals commonly rely on heuristics to simplify their decision-making procedures. While these mental shortcuts can be advantageous when decision-makers face time and data constraints, they can also result in systematic mistakes in decision-making (Tversky & Kahneman, 1974).

It is also noteworthy to mention that the dependence on heuristics and utilizing biases are not confined to non-experts. Even professional researchers are susceptible to similar biases when they engage in intuitive reasoning (Tversky & Kahneman, 1974).

Five main biases will be defined to clarify how heuristics influence human judgment and decision-making in the business context: Overconfidence bias, Representativeness bias, availability bias, Adjustment and Anchoring bias, and framing effect.

### *Overconfidence Bias*

Confidence plays a critical role in gaining achievement across various domains, including but not limited to business (Johnson & Fowler, 2011). An observable phenomenon in decision-making is that individuals tend to exhibit overconfidence bias (Berthet, 2022). Nevertheless, overconfidence can result in inaccurate evaluations, unfeasible anticipations, and dangerous decisions. Humans exhibit numerous psychological biases, but among the most persistent, potent, and prevalent is overconfidence (Johnson & Fowler, 2011).

The cognitive bias of overconfidence is a heuristic that refers to the tendency to have excessive confidence in one's cognitive abilities, intuition, decision-making, and judgment, without sufficient evidence to support such beliefs. The phenomenon of overconfidence leads individuals to overestimate their chances of success or expertness in a particular task or decision (Ahmad & Shah, 2022).

People with overconfidence bias tend to have three characteristics, which include overestimation, over-placement, and over-precision. Overestimation is when humans concentrate on their own abilities, overestimate their capabilities, and ignore their real functioning. Over-placement refers to people believing they are superior and more capable than others. Over-precision is when individuals are too confident about their decisions and ignore related risk indicators (Moore & Healy, 2008; Statman et al., 2006; Larrick et al., 2007; Odean, 1999, as cited in Ahmad & Shah, 2022).

Most individuals tend to overestimate their personal qualities and abilities, believing they have control over circumstances beyond their control and a feeling of invincibility toward risks. Overconfidence represents a prevalent aspect of human psychology that leads to expensive errors and misjudgments. So, it is unsurprising that overconfidence has been held responsible for numerous catastrophic events that garnered significant public attention throughout history, including financial crises (Johnson & Fowler, 2011).

An example of overconfidence bias in the business context is strategy team confidently believes that their chosen market entry strategy will result in instantaneous success and fails to consider potential risks and competitive challenges, leading to unforeseen setbacks and declined market share.

***Representativeness Bias***

By using the representativeness heuristic to judge how likely an event is to happen, key characteristics are compared to those of similar events that have been encountered before. This comparison is used to estimate the probability of the event. To assess the similarity of the event to other related events within the scope of human knowledge, If the event is very similar to these other events, humans tend to think it is more likely to happen (Tversky & Kahneman, 1982).

In terms of concept, the representativeness heuristic can be deconstructed into three components. Firstly, the regular subject of the class is viewed as representative of the entire group. The second component involves the comparison of the entity to the representative class to assess their similarity. The third and final component demonstrates the significant similarity between the entity and the class, implying a greater likelihood that the entity belongs to that category. In contrast, an insignificant similarity suggests a lower likelihood (Hjeij & Vilks, 2023). Tversky and Kahneman (1974) suggested that although the representativeness heuristic is typically used without much conscious effort and may appear convincing in numerous instances, the heuristic's third component often results in significant inaccuracies or, at the very least, biases. The base rate fallacy can be a consequence of utilizing the representativeness heuristic (Hjeij & Vilks, 2023).

People often rely on the representativeness heuristic when making probability decisions and assessing causality. This heuristic suggests that if two things, $\alpha$ and $\beta$, are similar in some way, it does not necessarily mean that $\alpha$ causes $\beta$ or vice versa. However, if $\alpha$ occurs before $\beta$ and is similar to $\beta$, people may assume that $\alpha$ caused $\beta$ (Hjeij & Vilks, 2023).

It can be inferred that even individuals with advanced cognitive abilities rely on the representativeness heuristic to make probabilistic decisions without explicitly utilizing their knowledge of probability. This method of appraising probability judgments can result in significant inaccuracies because representativeness is not impacted by various characteristics that influence probability assessments (Hjeij & Vilks, 2023).

An example of representativeness bias in the business context is a strategy team considering that a competitor's recent failure in a specific market indicates their overall strategy is flawed. This leads them to make strategic decisions based on this single sample rather than considering more comprehensive market dynamics and competitor abilities.

***Availability Bias***

In the realm of psychology, the concept of "availability" or "accessibility" refers to the easiness with which a particular opinion can be retrieved (Kahneman, 2012). In other words, people tend to estimate event frequency based on how easily relevant instances come to mind. Since introducing the heuristic, many studies have explored the influence of availability bias on the decision process (Pachur et al., 2012). When individuals make judgments about the possibility of an occurrence, they frequently rely on this type of heuristic. As a result, if a rare occasion is brought up repeatedly in everyday discussions and is easily recalled, it is more probable that individuals overestimate its probability (Kahneman, 2012).

Availability is a valuable signal for evaluating probability (Tversky & Kahneman, 1974). The availability heuristic is a method individuals employ to evaluate the level of risk involved by recalling whether instances of harm can be easily reminded (Kahneman et al., 2017). The availability heuristic has also been proposed to explain imaginary associations or irrelevant interdependence, where people mistakenly perceive two occurrences as connected when they are not (Tversky & Kahneman, 1973).

An example of availability bias in the business context is when developing a new strategic initiative, the strategy team relies heavily on data and success stories from past projects that align with their desired approach, overlooking alternative strategies and potential pitfalls.

***Adjustment and Anchoring Bias***

The anchoring effect pertains to the phenomenon in which an individual relies heavily on a piece of information or value (referred to as the anchor) when making subsequent judgments or estimates about a particular situation (Morewedge & Kahneman, 2010). Baron

(2000, as cited in Hjeij & Vilks, 2023) refers to the work of Tversky and Kahneman, describing that the anchor serves as the center of a circle, with a satisfactory range, and the most acceptable response is within that range, either up or down from the anchor.

The structure of the issue may propose the starting point, or it may emerge as a consequence of a partial calculation. In either scenario, modifications to the initial value are usually inadequate. This means that distinct starting points result in dissimilar approximations, tending to be influenced by the preliminary values. This occurrence is commonly known as anchoring. Anchoring happens not exclusively when the starting point is provided to the participant but also when the individual establishes their approximation of the outcome of an unfinished computation (Tversky & Kahneman, 1974).

The anchoring phenomenon has been observed and studied in various scholarly and practical contexts, including business negotiations, where negotiators often establish a fee anchor determining the satisfactory deal range. The anchor serves as the starting point from which the negotiators acquire the upper and lower limits of their bargaining range. This effect is persistent when the parties have limited time to make decisions and analyze their options (Hjeij & Vilks, 2023).

The influence of the anchor is noteworthy as it has the potential to deviate the numerical estimations of all involved sides, even if the anchor is illogical or unreasonable, and without their awareness of such a bias (Hjeij & Vilks, 2023). The issue arises as the mind is inclined to focus on the anchor and adapt accordingly, regardless of whether the anchor was presented in a direct or indirect style (Hjeij & Vilks, 2023).

An example of adjustment and anchoring bias in the business context is during the strategic planning process, the team sets overly optimistic performance targets, anchoring their expectations on best-case scenarios. This bias hinders objective evaluation and leads to the development of unrealistic strategic goals.

***Framing Effect Bias***

The experiment conducted by Tversky and Kahneman (1981) revealed a typical inclination among individuals to exhibit risk aversion when presented with a structure emphasizing gain and survivorship and risk-seeking behavior when exposed to a structure emphasizing loss and death. This phenomenon of a transformation in risk preferences based on different problem explanations is commonly referred to as a "framing effect" (Druckman, 2001).

The occurrence of framing effects in decision-making happens when the use of particular expressions in various contexts stimulates distinct responses or reactions, such as selecting “low risk” versus “high reward,” “90% effective” versus “10%”, or “Gain $100” versus “Avoid losing $100”. Framing effects often happen when alternative phrasing of a decision problem elicits distinct emotional responses. Decision-makers typically succumb to framing effects unless they can develop and acknowledge alternative frames and their incoherence (Morewedge & Kahneman, 2010). Hence, the way in which an issue is framed, such as through a focus on potential gains versus potential losses, can have a consequential effect on the decisions made by individuals (Berthet, 2022).

An example of framing effect bias in the business context is presenting a new strategic direction to stakeholders; the strategy team focuses on the potential gains and benefits, framing the initiative as an exciting opportunity while downplaying the associated risks and potential drawbacks. This biased framing may skew stakeholders' perceptions and influence decision-making in favor of the proposed strategy.

So far, how humankind evolved to make decisions have been analyzed. It also developed some heuristics to meet its needs during this process, but using such biases resulted in some sub-optimal results. These all clarify that leaving humans to make decisions based on the available massive data might not be the best option. Humans need to be supported by tools that are safe from such heuristics. Currently, the most capable option for humans is AI. The following section will discuss AI and its decision-making abilities.

## Artificial Intelligence

In the field of computer science, the definition of AI lacks a universally accepted standard. Generally speaking, AI is defined as the capability of systems to acquire knowledge from experience, adapt to fresh data, and execute tasks that typically require humanoid intelligence. The concept of AI and AI systems was first coined in the 1950s, and from that time on, the field has undergone periods of both success (known as "AI springs") and decline (referred to as "AI winters"). However, with the emergence and continued development of big data technologies, such as enhanced computing repositories and high-speed data processing devices, AI is undergoing a regeneration thanks to the accessibility and potential of big data (Duan et al., 2019).

Throughout the timeframe, there have been various fields of application where AI systems have been utilized, possibly due to the promising economic benefits of an efficacious system, such as industrial, business, and medical sectors. AI-based decision-making has been one of the pivotal uses of AI throughout its history (Duan et al., 2019). The impact of AI approaches on decision-making extends beyond simply enhancing results; it also encompasses the possibility for instantaneous reaction, machine automation, customization, advanced logic models, and access to a wider range of data sources to support the decision-making process, as well (Phillips-Wren et al., 2009).

First, the process of the initial attempts to incorporate AI and decision-making will be reviewed with historical background. These attempts started with the works of Herbert Simon and were later followed by new systems like expert systems, Decision Support Systems (DSS), and Intelligent Decision Support Systems (IDSS).

**Herbert Simon and First Steps of AI**

Herbert Simon collaborated with Allen Newell to develop a computer simulation model to emulate human decision-making. The result of their joint effort was the invention of the 'Logic Theorist,' a program developed in 1956 that had the capability to demonstrate logical statements expressed in symbolic language. This program was a pioneering innovation, as it was likely the first instance of an artificial program designed to imitate specific human logic capabilities for resolving genuine problems. Simon, Newell, and Shaw introduced the General Problem Solver (GPS) afterward as the first-ever AI-based program designed to tackle all problems using a unique, unified algorithm. While the GPS algorithm proved successful in solving highly-organized problems, it was unable to handle the intricacies and sophistication of real-world situations. Simon was optimistic that machines would be capable of performing tasks equivalent to those of a human being by 1965 (Gugerty, 2006; A. Newell et al., 1959; Vardi, 2012, as cited in Hjeij & Vilks, 2023).

**Intelligent and Expert Systems**

Intelligent systems are employed to denote those that imitate human cognitive abilities. These systems use AI technology to explain, gain knowledge, predict, and evaluate. This technology can be employed to develop human capacities, such as looking through vast and diverse databases for relevant information, analyzing unstructured data, and detecting correlations in information from multiple sources that may impact a decision (Phillips-Wren et al., 2009). The utilization of these systems can be especially valuable in addressing complex issues which contain a high degree of unpredictability, an abundance of information, and randomness (Phillips-Wren, 2012).

Expert systems are the first and most widely accepted types of intelligent systems to try to capture the knowledge of a human expert in a computer algorithm. Illustrating knowledge in these systems is executed symbolically through output regulation, structures, or semantic networks (Monostori, 2003). Expert systems were one of the initial offshoots of AI to have been successfully marketed and remain an expanding category of information systems. Numerous enterprises have utilized this technology to enhance efficiency and financial gains by making improved business decisions (Edwards et al., 2000).

**Decision support systems (DSS)**

DSS arose in the 1970s and underwent significant evolution over the following decade (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007). It has been acknowledged that DSS typically comprises an arrangement of input, operation, and product as a representation of the decision-making procedure. Furthermore, the decision-maker has been identified as a vital system element. Recently, the expression "Decision Support" has been developed to incorporate a broader range of technology support, including Business Intelligence (BI) and analytical tools, with or without certain characteristics that engage with the decision-maker. Making use of BI and analytics is a suitable way to solve issues concerning widely dispersed data and vast datasets, known as "Big Data" (Phillips-Wren, 2012).

An exemplary instance of a DSS is a closed-loop system that utilizes feedback to regulate its outcome (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

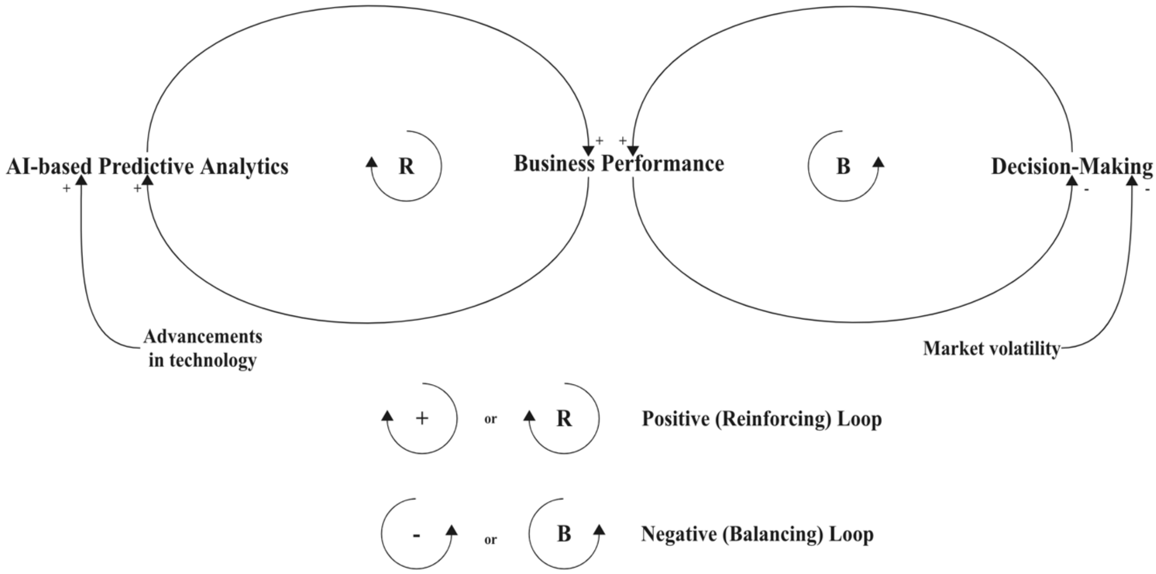
***Feedback Loops***

Numerous studies in psychology, economics, business, and related disciplines propose that learning occurs through uncomplicated negative feedback loops. These loops are commonly regarded as rapid, linear, and balancing, resulting in a constant harmonization to a state of equilibrium or an ideal result. However, the reality is far more complex than this simplistic view. Since its inception, system dynamics has underscored the multiloop, multi-stage, and nonlinear nature of the feedback systems that exist in our environment (Forrester, 1961, as cited in Sterman, 2000).

Contrary to popular belief, the most complex behaviors often emerge from the feedback interactions in the company of the various elements of a system rather than the complexity of the individual elements themselves. According to system dynamics, all dynamics originate from the interplay of two kinds of feedback loops: positive and negative loops. Positive loops are characterized by self-reinforcement, while negative loops exhibit self-correction. Positive loops tend to strengthen or intensify whatever occurs within the system, whereas negative loops work to counteract and resist change. The dynamics of entire systems originate from the interconnections between these networks of feedback loops. The feedback loops respond to the decision-makers' decisions in a way that may be expected or unexpected. These loops may include both positive and negative feedback mechanisms and encompass several state variables (known as stocks) and nonlinearities. Both ecological and societal systems exhibit a significant degree of systems complexity (Sterman, 2000).

**Figure 3**

*An example of a feedback loop diagram in DSS*[2]




*Note.* Adapted and modified from “Business dynamics: systems thinking and modeling for a complex world (p.183)” by J. Sterman, 2000, Irwin/McGraw-Hill. Copyright 2000 by The McGraw-HillCompanies. Adapted with permission.

***Observe, Orient, Decide, and Act (OODA) cycle***

Experts in the DSS field widely acknowledge Simon's model of the decision-making procedure. This model comprises four phases: intelligence, design, choice, and implementation. During intelligence, the decision-makers collect data and comprehend the

[2] The text explores the interplay between AI-based predictive analytics, business performance, and decision-making through two feedback loops. The positive loop illustrates how accurate predictions from AI-based analytics enhance decision-making, leading to improved business performance, which in turn generates more high-quality data for further analytics refinement. In contrast, the negative loop emphasizes that business performance serves as feedback for decision-making effectiveness, prompting adjustments and improvements in decision-making strategies to enhance business performance.

issues. They then determine indicators, evolve the model, and study potential paths in the design stage. The choice stage is the point at which the decision is made, and the implementation stage involves the decision maker taking action and gaining insight. The process's phases usually take place consecutively, with feedback loops placed between each stage. Academics working in the field of decision support have a preference for a four-step process called the OODA cycle, which stands for Observe, Orient, Decide, and Act (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

OODA loop, which is also referred to as the four-box method, is a procedure utilized to assist individuals in making decisions when confronted with an overabundance of data (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007). The OODA loop highlights several critical feedback mechanisms in the decision-making procedure, particularly the feedback generated by the environment following an action taken within it. Additionally, the OODA loop illustrates the straight feedback channels enabling information to flow from the decision and action phases to the observation step. Eventually, the OODA loop includes an indirect recommendation feedback loop that spreads from the orientation step to all other phases of the decision-making procedure. The explicit and implicit feedback mechanisms present alternative ways in the decision-making procedure, accelerating the speed at which the process iterates (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

AI strategies are usually chosen to demonstrate and resolve these complex issues, and the cooperation of AI and decision-support systems results in Intelligent Decision Support System (IDSS) (Phillips-Wren, 2012).

**Intelligent Decision Support Systems (IDSS)**

Unsurprisingly, scientists have tried to enhance decision-making by utilizing new technologies to improve and broaden human abilities. This objective has been achieved in several applications via advancements in AI (Phillips-Wren, 2012).

IDSS augments traditional DSS by incorporating AI operations, which assist clients in decision-making stages and duties, or provide additional abilities (Phillips-Wren et al., 2009). The capabilities of DSS in practical management contexts can be augmented through the utilization of AI, which enables the integration of diverse resources and increases the capacity for help (Rosenthal-Sabroux and Zarate´, 1997, as cited in Phillips-Wren et al., 2009).

IDSS has become progressively popular in numerous fields, such as business, economics, management, and healthcare. Different expressions are used in academic literature to describe systems like these, such as Expert Systems, Intelligent Decision Systems, and

Knowledge-Based DSS (Phillips-Wren, 2012). A significant body of literature demonstrates the potential of IDSS to enhance decision-making procedures and products (Phillips-Wren et al., 2009).

IDSS assists with cognitive duties by actively facilitating duty execution, analyzing and interpreting data to generate knowledge, and acquiring knowledge through experience (Phillips-Wren, 2012). In addition, IDSS can enhance the quality of decisions concerning their results. IDSS has been designed and assessed for its practical applicability in various real-world contexts (Phillips-Wren et al., 2009).

IDSS is a type of DSS that exhibits specific characteristics that are associated with "Intelligent Behavior" (Turban & Aronson, 1998; Phillips-Wren et al., 2009):

- master or comprehend past events;
- interpret unclear or conflicting information;
- React effectively and rapidly to a new circumstance;
- Utilize logic to solve issues;
- Manage challenging circumstances;
- Comprehend and conclude using logical methods;
- Use the information to manage the circumstances;
- Reflect and infer;
- Determinate the corresponding significance of various components in the circumstances.

Different frameworks have been suggested for IDSS. A general design divides the decision-making activities into three components: input, operation, and product, with feedback loops. The input module incorporates data expressly pertinent to the decision-making process and databases to direct the choice of possible decisions or assistance in results comprehension. In the processing module, the input is structured, predictions and suggestions are made, clarifications can be generated, and the "best solution" is determined within certain boundaries. In the output module, assessments may be declared, intensified, adjusted, and even employed as input for supplementary research (Phillips-Wren, 2012).

Two elements have significantly altered the character of decision support. They are expected to persist in shaping the future of IDSSs: (a) Worldwide businesses have a growing demand for decentralized data and the ability to make rapid decisions. (b) the widespread use of the internet has facilitated accessibility to decentralized data and has significantly increased the speed of decision-making processes (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

**AI Subfields in Decision-Making**

Speaking of AI technology and its application in decision-making, it is also vital to know which specific techniques and subfields of AI can be utilized in the desired area. The practical techniques will be presented here: Artificial Neural Networks, Fuzzy Logic, and Agents.

***Artificial Neural Networks (ANN)***

Artificial neural networks (ANN), referred to as neural networks or simply NN, constitute a category of models for nonlinear regression, discriminant, and data reduction that are intricately coupled and cooperate to address a challenge (Phillips-Wren, 2012). The motivation for NNs is rooted in investigating information-processing methods in the natural nervous structures, specifically the human brain. The system comprises a vast number of interrelated processing entities, commonly referred to as neurons, which work collaboratively to tackle distinct issues (Azadeh et al., 2007). NNs deliver an innovative computing framework in which problem-solving skills are acquired through a collection of samples (Bishop, 1994).

These helpful technologies provide ways to analyze massive volumes of data, gain knowledge from data, and recognize nonlinear relationships. Similar to how humans draw on their empirical findings and interpretation to make generalizations, NNs can do the same. As a result, they can make recommendations from indefinite and complex data (Phillips-Wren, 2012).

The considerable prevalence of ANN across numerous disciplines can be attributed primarily to their capacity for constructing complex nonlinear connections between input and output parameters through the utilization of training data (Baba & Suto, 2000). ANNs have been implemented in scenarios where there is a lack of established theoretical proof for the operational structures, making them predominantly data-driven instead of model-driven. The fundamental aspect of this approach is the unique arrangement of the information processing framework (Azadeh et al., 2007).

NNs have been widely applied in multi-criteria issues for over four decades (Gholamian et al., 2006). Although the applications of ANNs date back to the 1980s, they are presently at the front line of AI development (Duan et al., 2019). There has been a significant surge in the scale of study engagement in NNs, coupled with broad media attention (Bishop, 1994).

NNs are fundamentally distinct from a sequential, logic-based, programmed method since they are built on learning instead of a pre-programmed behavior (Phillips-Wren, 2012). NNs can use three principal approaches to comprehend a given function: supervised, unsupervised, and reinforcement learning. These techniques enable NNs to "learn" the procedure. In unsupervised learning, NNs are not given any outputs linked to their equivalent inputs. This type of learning aims to highlight any potential connections or links between data patterns. Contrarily, in supervised learning, the NN is given a data set including various inputs and the corresponding outputs. The NN then determines and changes the input weights to bring the NN's outputs as close as feasible to the intended outputs. Upon construction, the NN can forecast the result for a brand-new set of inputs, providing support for making decisions. Lastly, in reinforcement learning, the NN is given only a general assessment of its performance on a set of data instead of for each data point (Phillips-Wren, 2012).

ANNs can deliver models for a broad range of actual systems that are challenging to manage through conventional techniques (Baba & Suto, 2000). While a considerable amount of study has focused on generating essential principles and novel algorithms, there has also been a growing emphasis on the practical implementation of NNs in real-world scenarios (Bishop, 1994).

Lately, there has been a significant surge in interest in utilizing ANNs for different decision support systems, primarily due to their distinctive attribute (Baba & Suto, 2000). Systems that use this capacity to deduce meaning from past actions or patterns provide decision support that may fall outside the realm of algorithm-based approaches. NNs can produce a result that is as close to the desired outcome as desired for decision-making problems since they can estimate any limited continuous function with an error rate as minute as desired (Phillips-Wren, 2012).

In general, NNs can be considered potential solutions for issues that possess one or more of the following features:

- There exists a substantial amount of data that can be used for training the system;
- A basic fundamental principle or solution derived from an adequate model is challenging to establish;
- New data should be operated on rapidly due to a real-time restriction or because a considerable amount of data must be examined.
- The data operation procedure must exhibit resilience to moderate noise levels in the input information (Bishop, 1994).

***Fuzzy Logic Networks***

Even though NNs can roughly predict any ongoing and non-stop function and learn as they come across new input-output pairs, a couple of decision issues include inputs that are obscure, partial, imperfect, or indefinite (Phillips-Wren, 2012).

As reported in the literature, Lukasiewicz was the first to design fuzzy logic in the 1930s (Kumar et al., 2013). The roots of the fuzzy concept can be traced back to human reasoning, which capitalizes on abstract wisdom without limitations (Vinodh & Balaji, 2011). The primary motivation for employing fuzzy theory stems from inaccuracy and uncertainty in the problems (Kumar et al., 2013). Examination in the qualitative domain often struggles with imprecision where data cannot be precisely quantified as numerical values. Fuzzy logic offers a practical approach to addressing problems where an event involves inaccurate and indefinite values (Lin et al., 2006; Yang and Li, 2002, as cited in Vinodh & Balaji, 2011).

Fuzzy theory enables the handling of ambiguity linked to numerous parameters by allowing the description of a membership function over the range [0, 1] that marks the level of membership, where zero is totally incorrect and one is absolutely correct (Kumar et al., 2013). In specific decision-making scenarios, it can be helpful to have the capacity to define data points that are not strictly binary and confined to two distinct categories (Phillips-Wren, 2012).

Fuzzy logic has a significant benefit: it can be improved and tweaked as new data is acquired, giving consistent monitoring and control during the decision-making process. As fuzzy logic is employed to show the connections between variables in decision-making, nonlinear interactions naturally arise. Fuzzy logic offers a strategy for constructing and programming activities based on rule-based regulations. Expertise can be documented and made available to the person carrying out the decision-making process by codifying the knowledge of an expert into a set of regulations (Rajagopalan et al., 2003). Fuzzy logic encompasses several fundamental concepts, such as fuzzy sets, fuzzy if-then rules, and probability distributions (Vinodh & Balaji, 2011).

By integrating fuzzy logic and NN, a significant obstacle with employing NN for choice issues can be resolved by making the meaning of the decision variables more apparent, which is one of the main problems while using NN. It is feasible to imagine a connection between fuzzy sets and NN that would allow fuzzy sets to express decision inputs in a way that is understandable to humans. As a result, the individual responsible for making a decision would be in a better position to recognize the connection between the input and output, which would help to enrich their comprehension and knowledge while deciding. Another benefit is that the decision maker's pertinent information is simpler to use and integrate (Phillips-Wren, 2012).

Combining neural and fuzzy systems, termed a "complete integration," is an extremely effective strategy (Monostori, 2003).

***Agents***

The inadequacies of AI systems in the late 1990s and the recognition of the need for interconnection led to the emergence of a new field, Distributed Artificial Intelligence (DAI). This area of research is primarily focused on utilizing agent technology to facilitate interplay and intelligence, creating a bridge between humans and machines (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

Despite the success of AI methods such as ANNs, genetic algorithms, case-based reasoning, techniques from expert systems, and knowledge representation in the development of decision systems, intelligent agents (IA) have been found to be the most capable when it comes to tackling decision-making issues (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007). The description of an intelligent agent posited by (Wooldridge, 2009) is often regarded as the standard, describing it as a computer system positioned in a particular environment and equipped to act independently to reach its pre-defined goals. Also, an agent is described as a data processing system designed or developed based on human-centered principles and concepts (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

Prominent scholars argue that agent technology is an outcome of the integration of various computer science fields, including but not limited to object-oriented programming, decentralized systems, and artificial entity (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007).

It is possible to expand upon this definition by including qualities such as reactivity, proactivity, social ability, adaptability, cooperation, persistence, and mobility (Phillips-Wren et al., 2009). Reactivity and adaptiveness are capabilities that enable an IA system to recognize its environment and react to any alterations. Being proactive is an approach whereby the IA takes the initiative to act in order to achieve its predetermined goals. Social ability and cooperation enable communication skills with other entities, including negotiation and collaboration. Persistence grants IA the capacity to sustain a form over extended spans, while mobility grants them the opportunity to move throughout the system to accumulate expertise or accomplish tasks (Phillips-Wren, 2012).

Another crucial attribute of agents is their capacity to provide intelligent responses through collaboration and communication (Tweedale, Ichalkaranje, Sioutis, Jarvis, et al., 2007). In the early stages of human-machine collaboration, there was insufficient attention to the human factor and its cognitive procedures. This was mainly because of the immediate necessity for automation and quick and forceful implementation and presentation. To address these problems, recent developments in IAs have achieved approval as a promising solution. The human-resembling intelligence and decision-making of agent models make them a suitable choice to overcome such shortcomings (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

Groups of agents can achieve a balance between pursuing their goals and considering their environment, authorizing the production of more complex behaviors (Phillips-Wren, 2012). over the last few years, the concept of agent teaming has garnered widespread recognition. It has been classified as a significant area of focus termed as Multi-Agent System (MAS) within the field of computer science. Multi-agent teaming adopts ideas from human organizational patterns of collaborative work. Roles such as leadership, information exchange, collaboration, and interaction skills, play a vital role in the team's achievements. It is widely accepted that the structure of agent teaming should consider three critical characteristics: interaction, organization, and collaboration, as it is believed that They are crucial to agent teaming (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

Agent teams with varied intentions and purposes may act as proxies for decision-makers or other agents. Decision-makers can be assured that their demands and preferences have been considered when they receive recommendations, as the system has been developed to incorporate multiple perspectives and balance them accordingly. Additionally, the system may be programmed to make autonomous decisions, provided that certain limitations have been set (Phillips-Wren, 2012). To successfully form agent teams, three fundamental issues must be considered: communication, negotiation, and trust (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

Communication pertains to the various methods and channels through which agents can convey information to one another to enable mutual comprehension. The second challenge is Negotiation, which focuses on establishing agent teams. Typically, team building requires distinguishing the team's needs from those of individual agents. The third challenge is Trust, which necessitates determining how an agent should approach the issue of trust concerning other agents (Tweedale, Ichalkaranje, Sioutis, Urlings, et al., 2007).

In describing the intelligence of agents, scientists often discuss the characteristics a system must possess:

- Autonomy refers to the ability of an agent to function independently without human interference.
- Social ability refers to the capability of the agent to collaborate with other agents.
- Reactivity is the ability to recognize alterations in their surroundings and act accordingly.
- Pro-activeness, which demonstrates target-oriented conduct (Wooldridge, 2009).

## Systems Thinking

### Complexity and Systems Approach

The evolution and structure of humans' decision-making, biases and flaws, and the power of AI technology, its applications, and subunits in decision-making or decision support have been discussed so far. Now it may seem that applying AI to solve humankind's gaps in decision-making can be a very straightforward solution. However, in the following section, by making use of some principles of systems thinking, it is going to be discussed whether AI is capable of tackling every human decision-making issue or not.

Murray Gell-Mann has had an immense impact on complexity science in terms of his research revealing the connection between complex behaviors of systems and the basic regulations which resulted in these behaviors (Cabrera & Cabrera, 2019).

Gell-Mann (1988, as cited in Cabrera & Cabrera, 2019) proposed that a "systems approach" could explain many world components, not just biological systems. He suggested that this view could be beneficial in comprehending human-related organizations. Gell-Mann's (1995) work in the area of complexity had a substantial impact, bringing together a collective of systems thinkers who agreed that systems studies ought to progress cognitive and metacognitive skills or a deeper understanding of one's thinking systematically.

It has been postulated that complexity and systems thinking can provide us with a deeper comprehension of our CAS. In addition, human cognition, a crucial player in its decision-making, is believed to be a CAS (Cabrera & Cabrera, 2019).

Utilizing a complexity and systems perspective can help comprehend that transition energy is generated due to simple regulations employed across numerous levels within a system. This kind of contemplation is advantageous for leaders of giant, multi-layered firms (Cabrera and Cabrera 2019).

**Different Types of System Views**

Considering humans and businesses are built as complex systems, in the systems view, it is very crucial having an understanding of the human systems. So, while analyzing the capability of AI to tackle human decision-making, it is possible to have a precise knowledge of individuals' characteristics. The current and following section, "Evaluation of AI Implementation in Human Decision-Making Using Systems Thinking," are adapted from the book "Systems Thinking: Managing Chaos and Complexity: A Platform For Designing Business Architecture" by the famous systems thinking scholar (Gharajedaghi, 2011).

***Mindless System — A Mechanistic View***

The post-Renaissance mechanistic view in France argued that the world works like a machine with predictability determined by its fundamental principle and the natural principles of cause and effect, leading to the Industrial Revolution and the rise of mechanical management. It was proposed that organizations can be established like a complicated engine, with each part performing a single task.

The mechanical method of organization is straightforward and efficient, with a company being a mindless structure that serves no independent function. It is a platform with a mission determined by the user, and its performance standard is straightforward effectiveness. Its components are powerless, and it only works well when its environment is steady or has a negligible impact on it. This allowed for a generation-long capacity for producing goods and services that is greater than the sum total of human capacity.

***Uni-Minded Systems — A Biological View***

The biological way of thinking, which gave rise to the conception of an organization as a uni-minded system, arose primarily in Germany and Britain before gaining wide acceptance in the United States. The biological business structure model is considered single-minded, akin to a human, and declares that it has an intrinsic goal. The goal of open systems is to sustain their existence. It is widely accepted that living organisms must grow in order to survive.

In a business context, success is assessed based on the growth metric, typically considered the crucial performance indicator. Consequently, rather than perceiving profit as an ultimate goal itself, as is typically attributed to the mechanical mode, profit is seen as a means of achieving growth in the biological mode.

Even though uni-minded systems possess a degree of autonomy, their individual components do not. Indeed, the advantage of these systems is that their parts do not have the freedom of varying their reactions to the events in their environment, instead responding in a predetermined mode. A uni-minded system is managed exclusively by a unique central processor, known as the executive function. It is hypothesized that the disorder of any typical single-minded system results from either a deficiency of data or interference in the communication network. Nevertheless, if components of a system gain self-awareness and demonstrate preference, the system will be in serious problem. In circumstances where decision-making authority is distributed by exhibiting choice by components, tension is bound to arise. This necessitates strategies for resolving disputes, and paternalism has been identified as a typical mode of addressing such issues.

***Multi-Minded System — A Sociocultural View***

Social organizations demonstrate multi-minded systems. From a sociocultural perspective, the business is seen as a non-mandatory cooperation of purposeful individuals who consciously select desired results and the procedures to attain them. It is not possible to fully describe the behavior of a system whose components exhibit choice through the application of mechanical or biological models. A social system must be analyzed on its unique distinctions to be properly understood.

In this situation, the purpose is a crucial factor. Ackoff (1972, as cited in Gharajedaghi, 2011) argues that purposefulness can be identified by an entity's ability to generate identical results in varying conditions and diverse outcomes in identical or altered conditions. Even though the power of selection is essential for purposefulness, it is not enough to ensure it. A unit that has the potential to behave variably yet ultimately delivers the same result regardless of the conditions is not purposeful; it is goal-oriented. Human beings are known for their capacity to be purposeful. Businesses are integral components of society, playing a decisive role in pursuing larger objectives. The primary challenge of the system is to reconcile the interests of the parts with each other and that of the entire system.

As opposed to mechanical systems, in which the integration of elements into a unified entity is a single-step process, for social organizations, the integration challenge is an ongoing battle and a perpetual procedure. An organization's task is to satisfy its members' objectives while concurrently meeting its environment's demands. The individuals of a sociocultural group are connected by collective and mutually approved goals, as well as by the shared values that are inherent in their culture. Culture is a binding mechanism that ties the individual components together to form a unified unit.

**Evaluation of AI Implementation in Human Decision-Making Using Systems Thinking**

Considering discussed attributes, it can be deduced that humans, organizations, and businesses are purposeful, multi-minded complex systems. As discussed before, this study will analyze whether AI can solve humans' decision-making issues by considering AI attributes discussed before and by utilizing the five principles of openness, purposefulness, multidimensionality, emergent property, and counterintuitive behavior. It should also be remembered that these principles act collectively as an interactive whole.

***Openness***

Openness denotes that living (open) systems' actions can only be comprehended within the framework of their environments. The world is a dynamic, complex system. Realizing that although all components are interconnected or mutually dependent, it could be possible to divide them into two distinct classes: controllable elements and those beyond control.

The system, thus, comprises all the mutually influential sets of factors that players can control take part. The environment, however, comprises all the elements the system cannot control, though they still influence the system's behavior. A subsequent breakthrough was attained when individuals observed that, despite being beyond our control, the element's behavior in the environment was more or less foreseeable. Generally, the more unmanageable an environmental factor, the more probable it is to be foreseen. Controlling is understood to mean that an activity is both essential and adequate to generate the desired result. Influencing, in contrast, implies that the activity is only a contributing factor, not enough to bring about the desired outcome on its own.

As our understanding of the environment strengthened, our capacity to change the ungovernable factors to those that could be affected also improved. As humans got better at impacting a variable, they got worse at forecasting it. Previously, customers could be foreseen; however, they were out of control. Nowadays, they appear to be more vulnerable to impact; thus, their behavior is far less foreseeable. As it is being increasingly understood, actual control is quite limited in many situations; however, there is potential to have a considerable impact. Therefore, effective system management involves managing the associated transactional environment and leading those we cannot control. In other words, leadership is the capacity to affect people, regardless of having authority over them (Gharajedaghi, 2011).

**Result:** Reviewing openness property, one can see that AI can help humans improve accuracy and efficiency by processing large amounts of data, as complex systems and their environment interconnections can result in many variables. Nevertheless, considering prediction as one of the most expected attributes of AI (Phillips-Wren, 2012), one can see that openness property may be in contrast with this expectation; however, businesses can now manage their target groups, and they have less power of prediction on them. In addition, Although AI has the capability to analyze vast quantities of data, it may not be capable of comprehensively capturing the complexities of human values and cultural concerns.

***Purposefulness***

In order to have an impact on the participants involved in business, it is essential to comprehend "why they do what they do." Realizing the distinctions between information, knowledge, and understanding is essential. With information being concerned with “what,” knowledge focusing on “how,” and understanding being the “why” questions, they are distinct concepts. In order to be an effective player, it is necessary to reach a heightened level of understanding and comprehension of the reasons "why they do what they do." The “why question” inquires into the purpose of choice, which results from the dynamic interactions between the rational, emotional, and cultural components.

Rational choice is based on self-interest or the personal interests of the individual making the decision, which may not be wise or in the best interest of the collective. Rationality does not take into account the ethical indication of the decision or the potential outcomes of the action from a broader perspective. Businesses are operated by rational decision-making, with accomplishment determined by the ability to conform to the prevailing market norms; thus, advancement does not necessarily correlate with greatness. The emotional choice is where beautifulness and exhilaration reside.

The potential for exhilarating challenges is a significant factor in our decision-making, as it can bring a sense of purpose to life; without it, life would become mundane and uninspiring. In contrast to rational choice, which is guided by external values, the emotional dimension is characterized by an inherent focus on pleasure and happiness originating from the emotional condition itself. This distinction is highlighted by rational selection being risk-aversive, while emotional selection embraces risk as an essential part of the adventure and exhilaration.

Culture is a crucial element of the decision-making process, determining the ethical standards the decision-maker must adhere to it. These values act as a restraint, limiting the range of decisions that may be taken. Nevertheless, culture strongly influences the decision-making process by assigning default values. Purposeful behavior is driven by values often implicit within the culture and not consciously chosen by the decision-maker (Gharajedaghi, 2011).

**Result:** As discussed previously, AI, a data-driven tool, can cope well with rational situations. However, considering humans and organizations as purposeful complex systems, they include properties such as emotions, culture, values, and ethics. AI may struggle in this regard because these factors are frequently complex and context-dependent, and it may not be possible to assimilate or learn them in its decision-making process entirely.

***Multidimensionality***

Undoubtedly, multidimensionality is one of the most powerful concepts of systems thinking. It involves recognizing complementary connections between conflicting propensities and constructing viable entireties out of incompatible components. The pervasive notion that opposite propensity must be viewed as a zero-sum game has profoundly affected most societies. This rigid dichotomy is usually expressed as a binary, with one side being declared “right” and the other side “wrong.” It creates a win/lose battle, leading to further conflict. However, rather than this being the only way to resolve differences, it is possible to view opposing propensities on a continuum and achieve a settlement. This settlement is often a combination of two extremes, and while it may provide a provisional resolution, it is an inherently unsteady solution. As such, to effectively address social realities, it is essential to design new structures capable of resolving these opposing tensions.

The notion of multidimensionality entails that the conflicting forces are present and intertwined and construct a complementary union. This harmony is not limited to pairs but can involve more than two components. This phenomenon can be described as a non-zero-sum game in which the outcomes of both parties do not need to be mutually exclusive. That is, the change in one party's outcomes can be independent of the other, allowing for a situation in which both can increase or decrease at the same time. A multidimensional approach allows for examining the previously perceived dichotomies to explore how they can be synthesized together to create something entirely novel. The enlargement of dimensions permits the identification of novel perspectives in which the conflicting propensities can be comprehended as a single, integrated entity with its distinct rationale (Gharajedaghi, 2011).

**Result:** Multidimensional issues are frequently complex and challenging to resolve through conventional analytical methods. AI can address the property of multidimensionality, but it necessitates the utilization of suitable algorithms and data to accomplish this effectively.

As presented before, fuzzy logic can be an excellent candidate to tackle such problems as it can cope with non-binary properties.

***Emergent Property***

The notion of emergence is a pivotal principle in the science of complexity (Stacey, 2011). Emergent attributes are characteristics related to the whole, not the elements, and cannot be inferred from the characteristics of the parts. They must, however, be explained in their own terms since they are the result of interactions rather than the aggregate activities of the elements. They are also impossible to quantify directly and do not conform to any of the five human senses. If measuring is required, only their embodiment can be measured. Emergent features are fundamentally incapable of being analyzed or modified by analysis methods, and causal theories cannot explain them. Predictably, relying solely on an analytical approach does not result in a comprehensive explanation of emergent phenomena.

It has been proposed that interactions between various components result in emergent features. The interaction concept denotes a dynamic procedure that results in a time-dependent status. To put it another way, the emergent phenomenon is being recreated constantly, immediately, and instantaneously. Even storing or saving them for later use is impossible. Assuming emergent properties are the organic result of ongoing activities, one must realize the procedures that produce them to comprehend them.

Considering success as an emergent quality, supervising interactions instead of just actions is required. A successful team is defined by its participants' competency and the quality of their interactions with one another. The components' adaptability and mutually reinforcing interactions produce a stronger resonance than the total strength produced by the individual components. Incompatibility between the pieces, on the contrary, will lead to a less powerful strength than what the aggregate could have been capable of producing. Similar to this, a business can be a value-adding or value-reducing structure according to the types of interactions between its participants.

It was stated that emergent qualities could not be assessed straightaway; only their occurrences could be analyzed. However, measuring a phenomenon's embodiment has proven to be quite difficult. The capability of evaluating an organization's success has not always been simple. Growth has long been regarded as a crucial indicator of an organization's accomplishments because it expresses success. Most likely, a successful business will grow; nevertheless, just because a business is growing does not essentially indicate that it is successful (Gharajedaghi, 2011).

**Result:** The emergent property is the one that AI can show its least capacity to cope with it. Regarding previously discussed sections, the emergent property encompasses the emergence of new patterns and arrangements that may not be entirely predictable by AI, and it is frequently reliant on a range of contextual factors that may be challenging to model accurately. Emergent behavior may give rise to unanticipated outcomes that may be challenging to predict and regulate and difficult to explain or comprehend, even with the assistance of AI.

***Counterintuitive Behavior***

Gharajedaghi (2011) continues that the realm of social dynamics is full of counterintuitive behavior. Such behavior operates on a level of complexity that surpasses the limitations of an analytical approach. Counterintuitive behavior refers to the tendency of actions aimed at achieving a particular outcome to produce unintended or even opposite results. The objectives of a system may diverge from human purposes and may not be aligned with the choices of any singular actor operating in the system.

To gain a deeper understanding of counterintuitive behavior, it is essential to recognize the empirical implications of the following statements:

- The relationship between cause and effect can be set apart in time and space. It means that an occurrence that occurs at a particular time and place may have delayed consequences, influencing a different time and place altogether.
- The relationship between cause and effect can also be circular, with each one substituting the other in a constant feedback loop.
- An occurrence can have different results, with the relative significance of each effect potentially changing over time.
- A group of variables that originally had a significant part in causing a particular result may be substituted by a different group of variables later. As a result, eliminating the primary cause may not stop the effect entirely.

**Result:** AI can detect unexpected behaviors and results within a system by recognizing patterns and relationships in vast datasets. It can simulate a system's behavior and assess the influence of diverse variables, which can aid in recognizing and proposing solutions for counterintuitive behaviors. However, counterintuitive properties frequently encompass unexpected or unforeseen behaviors within complex systems, which may be challenging for

AI to forecast or model accurately. It can be due to human factors like emotions, biases, and emergent properties.

## Human-AI Relation in Decision-Making

### Decision-Making Levels

Undoubtedly, any business's prosperity hinges on its managers' aptitude to make wise decisions and do so promptly. Nonetheless, ascertaining the appropriate course of action is contingent upon the type of decision at hand and the decision-makers' characteristics (Edwards et al., 2000). As per Anthony's (1965, as cited in Edwards et al., 2000) classification, decision-making can be categorized into three levels that are highly correlated with different levels of managerial accountability. He coined the terms strategic planning, management control, and operational control to describe the three levels of decision-making. However, the terms strategic, tactical, and operational decisions are currently more commonly employed to refer to these levels.

Edwards et al. (2000) state that the objective of strategic planning is to safeguard the long-term sustainability and vitality of the enterprise as a cohesive entity, effectively outlining the objectives and identity of the organization. Strategic objectives are translated into specific aims and performance standards at the management control level, also known as tactical decision-making. In contrast to the strategic level, decision-making at the management control or tactical level is characterized by distinctly defined boundaries determined by the strategic decisions. Therefore, decisions at this level tend to be more well-planned. At the operational control tier, decision-making becomes even more specific and focused, with a restricted span of actions aimed at operating the routine responsibilities of individual divisions within the organization based on the standards set at the management control level. Decision-making remains highly structured and primarily based on the organization's data resources. It is worth noting that the boundaries between the three categories of decision-making - strategic, tactical, and operational - are often fluid and not always distinctly defined.

On the other hand, Turban and Aronson (1998) introduce another way decisions can be classified into three categories based on the level of predictability surrounding the problem definition and resolution: structured, unstructured, and semi-structured. A structured decision is one with a recognizable answer, while an unstructured determination relies on the individual decision-maker, with little to no consensus on the resolution. Unstructured decisions necessitate the use of determination on the part of the decision-maker, while structured decisions do not require such a characteristic. The choice of the individual making the decision is extremely influential when it is unstructured, as their selections and backgrounds impact the outcome. Semi-structured decisions, which lie between the extremes of structured and unstructured, are various issues that can be solved through analytical and data-driven approaches, attracting the most attention from technology (Phillips-Wren, 2012).

**Supporting Versus Replacement**

After introducing levels of decision-making in businesses, in the second stage, this study will discuss two distinctive and possible roles of AI in business decision-making: supporting and replacement, also known as augmentation and automation.

Developing further and including AI in the process chain as a principal data processing tool is essential. With the use of AI, it is possible to detect groups in the population that are most indicative of variation on a precise level, even though they are not discernible to human intuition. AI has the capacity to handle a vast number of combinations and classifications efficiently, as well as complex interrelationships represented by nonlinear functions. This workflow qualifies for enhanced data utilization and results in more reliable and impartial decisions. Despite removing humans from the AI-driven workflow, the objective of such automation should not merely be to lower expenses. Such an advantage would be minimal compared to the potential of AI delivering improved decision-making capabilities, leading to revolutionary advancements in productivity and the ability to execute new missions (Colson, 2019).

AI's functions have been categorized into different methods (Duan et al., 2019). Irrespective of the organizational level, AI can be created to serve two distinct roles: a supportive function, which involves providing guidance or recommending solutions to problems, and a replacement function, where the AI makes decisions itself (Edwards et al., 2000).

When functioning in a replacement capacity, the AI takes on the responsibility of making the ultimate decision instead of the client. However, it is essential to note that this does not certainly result in job displacement for human workers. A replacement AI often facilitates the task to be carried out by an individual with a lower level of expertise (Edwards et al., 2000). McAfee and Brynjolfsson (2017) present a cautionary inference indicating that reducing our dependence on expert decision-making and estimations is crucial. Their rationale for this assertion is founded on empirical evidence that reveals the effectiveness of modeling and testing over human expertise in decision-making. They argue that human decision-making is often overemphasized despite machines' superior performance in such instances.

Afterward, McAfee and Brynjolfsson (2017) pose an intricate question regarding the extent of human involvement in decision-making. Despite the empirical evidence strongly indicating that models based on data generally surpass human expert decision-making, this is only the case when the models and information are accessible and verified. Many organizations and businesses operate in a dynamic, unstable, and constantly evolving context, making it challenging to rely solely on models. There will permanently be numerous circumstances where the essential information is unavailable or a model has not been established or thoroughly tested and verified for new or altered circumstances.

As a crucial component of the theoretical model for Five Ways of Stepping, Davenport and Kirby (2015) advocated for integrating a human-machine strategy that prioritizes augmentation over automation. As articulated in their study:

- Employees tend to have negative sentiments towards automation while showing a proclivity towards augmentation.
- While the exact mechanisms can be utilized for both automation and augmentation, the underlying purposes behind the application of these technologies are opposed.

Miller (2018) asserts that decision-makers and managers who disregard these two assertions may confront significant challenges and formidable opposition when attempting to advance AI implementation projects in their businesses. He contends that in the current age of AI and Big Data, there is an urgent need to establish a new partnership between humans and machines, which would enable them to work collaboratively and supplement each other's abilities. Licklider (1960, as cited in Miller, 2018) authored a scholarly paper entitled "Man-Computer Symbiosis," in which he articulated the objective of facilitating collaboration between humans and computers for decision-making and managing complex scenarios without strict reliance on pre-established algorithms. Surprisingly during that nascent era, he observed that initial analyses demonstrated that the collaborative alliance would execute cognitive operations more effectively than humans can achieve independently.

When operating in a supportive capacity, an AI can be developed to aid non-professionals or, sometimes, professionals. In this context, AI supports human decision-makers by offering guidance but does not substitute for them. Ultimately, the human is still responsible for making the final decision (Edwards et al., 2000). The assistance of human beings is indispensable in elucidating AI-generated results. In the context of business and organizations, it is frequently imperative to provide a rationale for the suggestions, decisions, or projections made by an AI system or machine for different types of inner and outer assessments and other purposes (Daugherty & Wilson, 2018). The AI systems or machines function as supportive tools, allowing humans to accomplish tasks beyond their innate capabilities and creating the fantasy of possessing "superpowers" (Miller, 2018).

Miller (2018) continues that despite the significant publicity given to the effects of technology on the business environment, many business professionals tend to overlook the fact that the substantial advancement in forming and implementing practical AI systems in previous years has happened concurrently with a substantial advancement in comprehending the character and essence of human decision-making. McAfee and Brynjolfsson (2017) express that the findings arising from these collateral advancements necessitate organizations and businesses to reconsider appropriately incorporating human intelligence into machine-based decision-making systems. This approach should be based on the new capabilities of machine intelligence and our enhanced comprehension of nature, both the ableness and boundaries of human intelligence. The intelligence of human decision-making and algorithms function concurrently.

It is crucial to establish new dimensions of collaboration between humans and machines to harness the potential of the latest versions of intelligent machines. This collaboration should aim to expand and enhance humans' intrinsic and unique abilities to improve business and organizational capacities in terms of adjustment and efficiency (Miller, 2018). Wilson and Daugherty (2018) explain that through their investigation of 1,500 firms, it has come to our attention that the most substantial enhancements in performance are observed when individuals and automated systems collaborate seamlessly. This form of collective intelligence enables humans and AI to amplify each other's distinct and supporting robustness synergistically. Humans bring their exceptional abilities in leadership, partnership, innovation, and interpersonal skills to the table, while AI offers unparalleled velocity, expansion, and analytical skills.

By virtue of their nature, humans possess the ability to be resilient, adjustable, and progressive, although not always exhibiting stability or effectiveness. Machines are deliberately developed to exhibit exceptionally effective and stable performance; however, their capability to comprehend uncertainty and react to swiftly altering conditions is restricted. Despite the ongoing development of AI technologies and their employments, humans will remain more flexible, adjustable, and skilled at interpreting unmeasurable conditions. Humans are also more competent in creating opinions and probabilities that do not depend on previous experience or accessible information. The capacity of humans to develop amidst alterations remains pivotal. On the other hand, intelligent machines are essential in facilitating rapid progress, extensibility, and high efficiency (Miller, 2018).

McAfee and Brynjolfsson (2017) note that some cutting-edge businesses are testing an "inverted partnership" between human cognition and machines powered by data and algorithms. The inversion they propose works accordingly: instead of the conventional collaboration standard, in which the machine supplies data as intake to human decision-making, the new approach involves the human delivering their decision-making as intake to the machine's algorithm. They envision the general approach for incorporating human cognition into ever-more smart machines accordingly: Allowing algorithms and machines to make decisions if feasible, providing sufficient information, samples, and accurate verification, and occasionally incorporating human decision-making as intake and allowing individuals to set aside algorithmic and computer-generated judgments when circumstances are considered exceptional, unique, or unfamiliar. They stress the significance of holding individuals and machines responsible for their decisions and determinations. They highlight the importance of tracking and evaluating the quality of decisions for both the machines and the humans utilizing the system.

### *What Type of AI Implementation Fits Each Decision-Making Level*

So far, it is argued that AI in decision-making can have two distinct roles: supportive and replacement. Furthermore, problems and levels of decision-making in the business fields can be categorized as operational, tactical, and strategic. Below it will be concluded that based on every specific type of decision-making level, which application of AI is more suitable to implement?

Edwards et al. (2000)evaluated expert systems for business decision-making at various categories and functions, drawing on studies conducted in the past twenty years. In their research, the various functions of AI, such as those performed by expert systems, were analyzed concerning the three levels of decision-making within companies: strategic, tactical, and operational. The results of the analysis revealed that:

- AI is applicable across various administrative levels. However, they are likely to be more efficacious and simpler to establish when utilized at the operational rather than the strategic level.
- AI operating in a replacement capacity are efficacious at the operational and tactical decision-making echelon. However, they are constrained in their functionality regarding the strategic level.

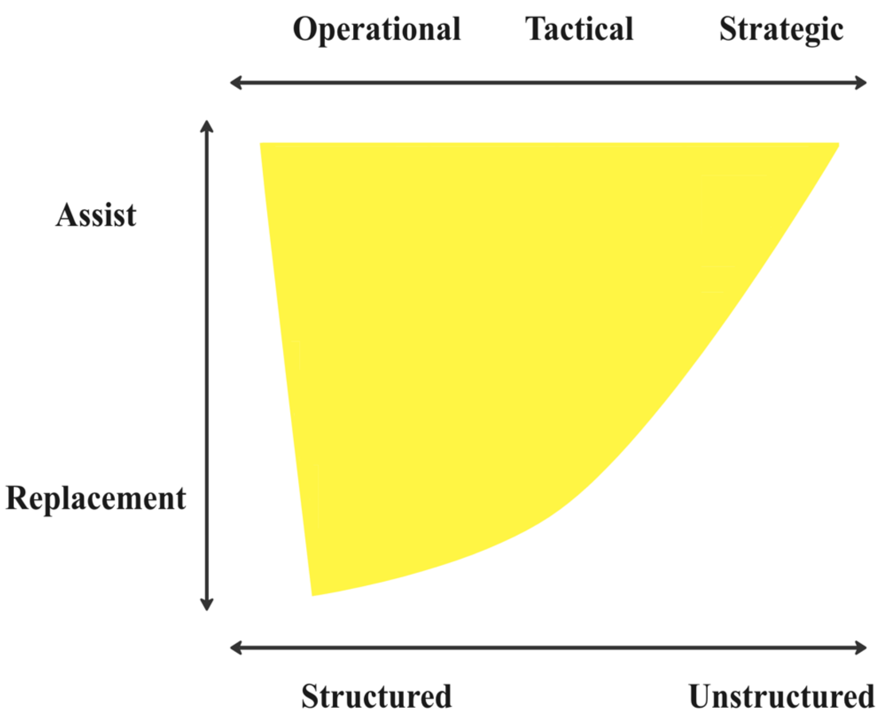
- AI functioning in a supportive capacity can assist clients in making improved decisions at all three levels of decision-making. However, the usefulness of these systems is contingent upon the clients' utilization of them.
- While an AI operating in a supportive capacity may not indeed be a time-saver for clients, an ES functioning in a replacement capacity can increase the productivity of decision-making.
- The individuals who utilized AI in a supportive function did not perceive any personal improvement in knowledge or skills due to interacting with the system.
- When transitioning from effectivity to productivity, businesses must recognize that an AI operating in a supportive capacity may not always enhance the performance of a decision-maker.

It is generally acknowledged that strategic planning decisions are typically unstructured. On the other hand, operational control decisions tend to be more structured (Edwards et al., 2000). Decisions exclusively dependent on structured data can be more efficiently assigned to AI, as AI is less susceptible to cognitive bias than individuals (Colson, 2019). Substituting executives and managers for strategic planning decisions are seemingly unfeasible, and generating an effective advisory system to support such decisions is challenging due to the elevated uncertainty and complexity that characterizes this level. In essence, it can be inferred that the number of operational control decisions surpasses that of strategic planning decisions. In addition, the majority of employees involved in making such decisions are typically situated in the more inferior managerial ranks, as opposed to the upper ones. It is not unexpected, hence, that there is a greater abundance of AI geared toward the operational decision-making level (Edwards et al., 2000).

In the event that an AI operates within the same field but fulfills distinct roles, the knowledge base of an AI functioning as a supporter must be distinct from that of an AI operating as a substitute for human decision-making. The knowledge repository of an expert advisory system should encompass a broad spectrum of issues that clients may encounter and offer practical assistance in more challenging circumstances. Therefore, developing an advisory AI may necessitate more exertion than creating an AI intended for replacement purposes (Edwards et al., 2000).

***Figure 4***

*AI's ability for implementation in different decision-making levels framework-Filled version*




*Note.* An approximate illustration of the range of businesses' decision-making and problems levels, and the corresponding possibility of implementing assistant or replacement AI

**Possible Humans' Positions in AI-Implementation**

Finally, based on the discussed decision-making levels and different approaches to problem-solving in business and organization, it can be offered that AI can be implemented in different stages, ranging from mere assistance to replacement. The four management models generated have distinct characteristics depending on the scope and type of human intervention: HITL (Human in the Loop), HITLFE (Human in the Loop for Exceptions), HOTL (Human on the Loop), and HOOTL (Human Out of the Loop) (Ross & Taylor, 2021).

***HITL***

Human in the loop (HITL): A machine helps the person. In this approach, humans make decisions, while machines simply support human decision-making or partially automate particular decisions or portions of decisions. It is commonly known as intelligence amplification (IA).

***HITLFE***

Human in the loop for exceptions (HITLFE): This model operates with an automated decision-making process, wherein the individuals only intervene in exceptional cases. The system necessitates some degree of discernment or input from the individuals to conclude; however, the human will likely not be called upon to make the entire decision. Additionally, humans are responsible for establishing the criteria which will mark certain exceptions for further consideration.

***HOTL***

Human on the loop (HOTL): This approach combines automation with human oversight, where the machine is responsible for performing the micro-level decisions while the human checks the results and provides feedback to modify the rules and parameters for prospective decisions. Additionally, it is possible to implement a more developed setup where the machine can suggest rules or variables that a person must first accept.

***HOOTL***

Human Out of the Loop (HOOTL): According to this model, humans are responsible for tracking the machine, only interfering with setting new constraints and objectives. Automation is used to facilitate continual improvement in the form of closed-loop adjustments derived from individual feedback.

## Limitations and Ethical Issues of Using AI in Decision-Making

This study primarily focused on examining the characteristics and benefits of integrating and utilizing AI in the context of business decision-making. However, it is essential to acknowledge that certain shortcomings and challenges are associated with this practice, warranting further analysis and discussion. Notwithstanding the escalating doubts surrounding the deployment of AI, only restricted triumph has previously been accomplished in the realm of prediction. This could be attributed to the problematic nature of generating precise predictions. Even with the aid of intelligent methods, including ANNs, genetic algorithms, and others, one would encounter significant challenges in generating trustworthy forecasts (Baba & Suto, 2000).

AI exhibits considerable potential for various ethical concerns (Coeckelbergh, 2019). Ethical issues encompass a wide range of distinctive characteristics and probabilities of happening. One of the principal ethical concerns consistently highlighted and extensively referenced pertains to privacy and data protection (Stahl, 2021). These interconnected AI systems are susceptible to malicious intentions, such as cybercrime. Moreover, the reliance on AI and other information systems on tangible material infrastructures introduces a potential vulnerability. These technological systems are not solely comprised of intangible code but are intricately intertwined with material components, rendering them susceptible to disruption or destruction (Coeckelbergh, 2019).

Numerous AI methodologies, which have significantly contributed to the remarkable advancements in AI, rely heavily on ANNs. The inherent attributes of these approaches that engender ethical considerations primarily involve ambiguity, unpredictability, and the indispensable requirement of vast datasets to effectively train the associated technologies (Stahl, 2021). Specific AI systems are not equipped to articulate the logical method involved in decision-making, leading to the “Blackbox” problem (Davenport & Ronanki, 2018, as cited in Duan et al., 2019). NNs are a typical example of a "black box" system because they can provide outcomes that mirror the training data. However, it is challenging to understand how they make decisions. It is mainly because computation is scattered among nodes and hidden layers, and it might get even more complicated if redundant networks are used. The advantages of interpretability should be evident to decision-makers to help them comprehend the correlations between inputs (i.e., decision variables) and outputs (i.e., decisions taken) (Phillips-Wren, 2012). Another example of AI deficiencies was that the clients of an assisting ES expressed a lack of belief in their ability to acquire knowledge by utilizing the system (Edwards et al., 2000).

The other cluster of ethical issues encompasses those associated with what was referred to as AI as connecting socio-technical systems. These systems were proposed to exhibit notable attributes such as independence, societal influences, and manipulative tendencies. The primary array of challenges stemming from inhabiting a digital world is intricately linked to the economy. The most prominent issue within this realm is undoubtedly the unemployment predicament. Although this pessimistic projection has not yet happened, there is a prevailing apprehension that AI will adversely affect employment dynamics (Stahl, 2021). Numerous authors caution against the potential consequences of unemployment and raise the inquiry regarding the necessity of restructuring our social institutions (Coeckelbergh, 2019). The economic consequences of AI extend beyond the realm of employment. Another critical problem revolves around the concentration of economic power, which subsequently has implications for political power (Stahl, 2021).

Furthermore, an issue that assumes particular significance in the context of AI is responsibility attribution. Given that technologies lack moral agency and are therefore devoid of responsibility, the other alternative to ensuring responsible conduct falls upon human agents. However, when it comes to technological activities, ascribing moral responsibility becomes notably challenging due to the inherent predicament known as the situation of "many hands" (Coeckelbergh, 2019).

Such issues highlight the importance of considering monitoring regardless of how much human involvement there is. Monitoring ensures the decision-making is “good” or at least fit for purpose while creating the data needed to spot problems and systematically improve the decision-making over time. Measuring decision-making effectiveness is also crucial: Recording at least two indicators that measure how appropriate decisions are made is important. There is always a trade-off in any business world's choice; maximizing it by relying on just one indicator is impossible. Furthermore, details about the decision-making process should be recorded, not simply the final result. This enables the efficient justification of "poor" decisions and the fitting of less-than-ideal results into the particulars of the decision-making process. Lastly, business products should be linked to the decision-making process (Ross & Taylor, 2021).

## Conclusion

In conclusion, this master thesis has explored the transformative role of AI in business decision-making, focusing on its potential benefits, challenges, and the dynamics of human-AI collaboration. While AI has the potential to enhance decision-making processes, it is essential to recognize the limitations and considerations that arise when applying AI in complex systems such as businesses.

This study has shown that businesses exhibit characteristics of complex systems, which are unpredictable, interconnected, and operate within a dynamic environment. Moreover, this research has highlighted the complex and multifaceted nature of decision-making processes within organizations. Classifying decisions into operational, tactical, and strategic or the range of structured to unstructured categories has shed light on the complexity and diversity of challenges decision-makers face. Understanding the nuances of decision complexity is crucial for effectively implementing AI in business decision-making.

The analysis revealed that AI has the immense potential to enhance decision-making processes by leveraging its ability to process vast amounts of data and uncover valuable insights. Although AI subfields, including ANNs, fuzzy logic networks, and agents, have made significant advancements in decision-making, they still face challenges when dealing with the complexity and human interplay inherent in business systems.

The findings indicate that AI excels in operational decisions and can be a practical assistant or replacement tool. However, as decisions move towards the tactical and strategic levels, AI's automation capabilities decline significantly, and its ability to fully replace human decision-making is limited. Strategic decisions, often involving unstructured data and high-level planning, require a nuanced understanding of the business context, human expertise, and judgment that current AI technologies cannot fully emulate.

Therefore, considering the duality of augmentation and automation, a balanced approach is necessary. Humans should be equipped with AI tools to augment their decision-making capabilities rather than completely outsourcing the process to machines. By leveraging AI as a supportive tool, businesses can benefit from enhanced analysis, data-driven insights, and improved decision-making at various levels.

It is crucial to acknowledge that the effectiveness of AI in decision-making depends on the specific context and the types of decisions being made. Businesses should carefully evaluate the nature of their decisions, considering factors such as complexity, data availability, and the need for human expertise. This evaluation will help determine the appropriate level of AI integration and the extent to which human judgment and critical thinking should be augmented.

In summary, while AI offers promising advancements in decision-making, it is not a one-size-fits-all solution. Businesses should strategically incorporate AI technologies to recognize their strengths and limitations, to optimize decision-making processes in an increasingly complex and data-driven business environment.

## References


Ahmad, M., & Shah, S. Z. A. (2022). Overconfidence heuristic-driven bias in investment decision-making and performance: Mediating effects of risk perception and moderating effects of financial literacy. *Journal of Economic and Administrative Sciences*, *38*(1), 60–90. https://doi.org/10.1108/JEAS-07-2020-0116

Azadeh, A., Ghaderi, S. F., Anvari, M., Saberi, M., & Izadbakhsh, H. (2007). An integrated artificial neural network and fuzzy clustering algorithm for performance assessment of decision making units. *Applied Mathematics and Computation*, *187*(2), 584–599. https://doi.org/10.1016/j.amc.2006.08.092

Baba, N., & Suto, H. (2000). Utilization of artificial neural networks and the TD-learning method for constructing intelligent decision support systems. *European Journal of Operational Research*, *122*(2), 501–508. https://doi.org/10.1016/S0377-2217(99)00250-7

Berthet, V. (2022). The Impact of Cognitive Biases on Professionals' Decision-Making: A Review of Four Occupational Areas. *Frontiers in Psychology*, *12*, 802439. https://doi.org/10.3389/fpsyg.2021.802439

Bishop, C. M. (1994). Neural networks and their applications. *Review of Scientific Instruments*, *65*(6), 1803–1832. https://doi.org/10.1063/1.1144830

Cabrera, D., & Cabrera, L. (2019). Complexity and Systems Thinking Models in Education: Applications for Leaders. In M. J. Spector, B. B. Lockee, & M. D. Childress (Eds.), *Learning, Design, and Technology* (pp. 1–29). Springer International Publishing. https://doi.org/10.1007/978-3-319-17727-4_101-1

Chimera, A. (2023, April 7). *How artificial intelligence can inform decision-making*. The Enterprisers Project. https://enterprisersproject.com/article/2023/4/ai-decision-making

Coeckelbergh, M. (2019). Artificial Intelligence: Some ethical issues and regulatory challenges. *Technology and Regulation*, 31-34 Pages. https://doi.org/10.26116/TECHREG.2019.003

Colson, E. (2019, July 8). What AI-Driven Decision Making Looks Like. *Harvard Business Review*. https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like

Daugherty, P. R., & Wilson, H. J. (2018). *Human + Machine: Reimagining Work in the Age of AI*. Harvard Business Press.

Davenport, T. H., & Kirby, J. (2015, June 1). Beyond Automation. *Harvard Business Review*. https://hbr.org/2015/06/beyond-automation

Dordevic, M. (2022, August 23). *Council Post: How Artificial Intelligence Can Improve Organizational Decision Making*. Forbes. https://www.forbes.com/sites/forbestechcouncil/2022/08/23/how-artificial-intelligence-can-improve-organizational-decision-making/

Druckman, J. N. (2001). Evaluating framing effects. *Journal of Economic Psychology*, *22*(1), 91–101. https://doi.org/10.1016/S0167-4870(00)00032-5

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Edwards, J. S., Duan, Y., & Robins, P. C. (2000). An analysis of expert systems for business decision making at different levels and in different roles. *European Journal of Information Systems*, *9*(1), 36–46. https://doi.org/10.1057/palgrave.ejis.3000344

Gell-Mann, M. (1995). What is complexity? *Remarks on simplicity and complexity by the Nobel Prize-winning author of* The Quark and the Jaguar. *Complexity*, *1*(1), 16–19. https://doi.org/10.1002/cplx.6130010105

Gell-Mann, M. (2002). What Is Complexity? In A. Q. Curzio & M. Fortis (Eds.), *Complexity and Industrial Clusters* (pp. 13–24). Physica-Verlag HD. https://doi.org/10.1007/978-3-642-50007-7_2

Gharajedaghi, J. (2011). *Systems thinking: Managing chaos and complexity: a platform for designing business architecture* (3rd ed). Morgan Kaufmann.

Gholamian, M. R., Fatemi Ghomi, S. M. T., & Ghazanfari, M. (2006). A hybrid intelligent system for multiobjective decision making problems. *Computers & Industrial Engineering*, *51*(1), 26–43. https://doi.org/10.1016/j.cie.2006.06.011

Glouberman, S., & Zimmerman, B. (2002). *Complicated and complex systems: What would successful reform of medicare look like?* Commission on the Future of Health Care in Canada.

Gordon, C. (2021, April 26). *Why Complexity Science Has Relevance To Building AI Leadership Brain Trust?* Forbes. https://www.forbes.com/sites/cindygordon/2021/04/26/why-complexity-science-has-relevance-to-building-ai-leadership-brain-trust/

Hjeij, M., & Vilks, A. (2023). A brief history of heuristics: How did research on heuristics evolve? *Humanities and Social Sciences Communications*, *10*(1), 64. https://doi.org/10.1057/s41599-023-01542-z

Johnson, D. D. P., & Fowler, J. H. (2011). The evolution of overconfidence. *Nature*, *477*(7364), 317–320. https://doi.org/10.1038/nature10384

Kahneman, D. (2012). *Thinking, fast and slow*. Penguin Books.

Kahneman, D., Slovic, P., & Tversky, A. (2017). Judgment under Uncertainty: Heuristics and Biases. In *Judgment under Uncertainty* (24. printing). Macat Library.

Kauffman, S. A. (1995). *At home in the universe: The search for laws of self-organization and complexity*. Oxford University Press.

Kumar, D., Singh, J., Singh, O. P., & Seema. (2013). A fuzzy logic based decision support system for evaluation of suppliers in supply chain management practices. *Mathematical and Computer Modelling*, *58*(11–12), 1679–1695. https://doi.org/10.1016/j.mcm.2013.07.003

McAfee, A., & Brynjolfsson, E. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. W. W. Norton & Company.

Miller, S. M. (2018). *AI: Augmentation, more so than automation*.

Monostori, L. (2003). AI and machine learning techniques for managing complexity, changes and uncertainties in manufacturing. *Engineering Applications of Artificial Intelligence*, *16*(4), 277–291. https://doi.org/10.1016/S0952-1976(03)00078-2

Morewedge, C. K., & Kahneman, D. (2010). Associative processes in intuitive judgment. *Trends in Cognitive Sciences*, *14*(10), 435–440. https://doi.org/10.1016/j.tics.2010.07.004

Mowles, C. (2014). Complex, but not quite complex enough: The turn to the complexity sciences in evaluation scholarship. *Evaluation*, *20*(2), 160–175. https://doi.org/10.1177/1356389014527885

Pachur, T., Hertwig, R., & Steinmann, F. (2012). How do people judge risks: Availability heuristic, affect heuristic, or both? *Journal of Experimental Psychology: Applied*, *18*(3), 314–330. https://doi.org/10.1037/a0028279

Phillips-Wren, G. (2012). AI TOOLS IN DECISION MAKING SUPPORT SYSTEMS: A REVIEW. *International Journal on Artificial Intelligence Tools*, *21*(02), 1240005. https://doi.org/10.1142/S0218213012400052

Phillips-Wren, G., Mora, M., Forgionne, G. A., & Gupta, J. N. D. (2009). An integrative evaluation framework for intelligent decision support systems. *European Journal of Operational Research*, *195*(3), 642–652. https://doi.org/10.1016/j.ejor.2007.11.001

Rajagopalan, A., Washington, G., Rizzoni, G., & Guezennec, Y. (2003). *Development of Fuzzy Logic and Neural Network Control and Advanced Emissions Modeling for Parallel Hybrid Vehicles* (NREL/SR-540-32919, 15006009; p. NREL/SR-540-32919, 15006009). https://doi.org/10.2172/15006009

Reeves, M., Levin, S., Fink, T., & Levina, A. (2020, January 1). Taming Complexity. *Harvard Business Review*. https://hbr.org/2020/01/taming-complexity

Ross, M., & Taylor, J. (2021, November 10). Managing AI Decision-Making Tools. *Harvard Business Review*. https://hbr.org/2021/11/managing-ai-decision-making-tools

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 99–118.

Stacey, R. D. (2011). *Strategic management and organisational dynamics: The challenge of complexity to ways of thinking about organisations* (6th ed). Financial Times Prentice Hall.

Stahl, B. C. (2021). Ethical Issues of AI. In B. C. Stahl, *Artificial Intelligence for a Better Future* (pp. 35–53). Springer International Publishing. https://doi.org/10.1007/978-3-030-69978-9_4

Sterman, J. (2000). *Business dynamics: Systems thinking and modeling for a complex world*. Irwin/McGraw-Hill.

Turban, E., & Aronson, J. E. (1998). *Decision Support System and Intelligent Systems*. Prentice Hall.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), 207–232. https://doi.org/10.1016/0010-0285(73)90033-9

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. *Science*, *211*(4481), 453–458. https://doi.org/10.1126/science.7455683

Tversky, A., & Kahneman, D. (1982). Availability: A heuristic for judging frequency and probability. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under Uncertainty* (1st ed., pp. 163–178). Cambridge University Press. https://doi.org/10.1017/CBO9780511809477.012

Tweedale, J., Ichalkaranje, N., Sioutis, C., Jarvis, B., Consoli, A., & Phillips-Wren, G. (2007). Innovations in multi-agent systems. *Journal of Network and Computer Applications*, *30*(3), 1089–1115. https://doi.org/10.1016/j.jnca.2006.04.005

Tweedale, J., Ichalkaranje, N., Sioutis, C., Urlings, P., & Jain, L. (2007). Building a decision making framework using agent teams. *Intelligent Decision Technologies*, *1*(4), 175–181. https://doi.org/10.3233/IDT-2007-1401

Vinodh, S., & Balaji, S. R. (2011). Fuzzy logic based leanness assessment and its decision support system. *International Journal of Production Research*, *49*(13), 4027–4041. https://doi.org/10.1080/00207543.2010.492408

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*(4), 114–123.

Wooldridge, M. J. (2009). *An introduction to multiagent systems* (2nd ed.). Wiley.