SELINUS UNIVERSITY
OF SCIENCES AND LITERATURE

THE USE OF ARTIFICIAL INTELLIGENCE PROGRAMMES TO HELP SPEED UP DECISION-MAKING

By Sailesh Dhanji Halai

2022

Declaration

I, Sailesh Dhanji Halai, attest that I am the sole author of this thesis and that its contents are only the result of reading and the research I have done.

Student ID: UNISE1650IT

Dedication

I sincerely dedicated this Thesis to my wife, children, family and friends; your patience, love, care, encouragement and support are all the sources of inspiration to complete this study.

Acknowledgement

First and foremost, I thank my supervisor, Dr Salvatore Fava, for his invaluable advice, support, and guidance during my PhD study. I would also like to thank Selinus University and its member for allowing me to conduct this research. A big THANK YOU also goes to Raluca Artimon, Adanna Bilwai, Armando Bonilla, Kenneth Pacis, Meeta Patel, Katarzyna Suder, Thomas Vernenne and Demetris Zafirelis for their encouragement and support all the time during this academic research. I want to thank all the participants who took the time to complete and return the survey. And my most enormous thanks to my family for all the support you have shown me throughout this research.

Abstract

This research aims to analyse the positive and negative impact of Artificial Intelligence (AI) on decision-making to speed up organisational workplace management. Moving ahead, Time, how soon the business requires a decision, and complexity are the two most essential factors in determining whether or not a decision can or should be automated, enhanced, or assisted by AI. Timing refers to how long it takes for an organisation to decide and implement it after becoming aware of a problem or an opportunity. High-frequency trading may occur in microseconds, but salary decisions might take weeks or months to implement. We will address all the objectives and questions mentioned below and accomplish them effectively, supporting the methods and techniques. In other words, it can be said that AI plays a vital role in determining people's capacity to evaluate and solve problems and gain knowledge through experience. Machines may be programmed to mimic human intelligence if given the correct data and instructions, known as artificial intelligence (AI). What we mean when we talk about "human intelligence" is the capacity of human beings to think, comprehend, apply logic, come up with clever solutions to problems, make sound judgments, and generalise knowledge from one context to another. The uniqueness of human intellect, among other things, resides primarily in the capacity for conscious thought.

Contents

Dedication 2

Acknowledgement 3

Abstract 4

Chapter 1: Introduction 10

1.1. Background 10

1.1.1. Artificial Intelligence Decision-Making 12

1.1.2. Artificial Intelligence help in decision-making 14

1.2. Research Problem 15

1.3. Research Questions 16

1.4. Research Aims and Objectives 16

1.4.1. Research Aims 16

1.4.2. Research Objectives 16

Chapter 2: Literature Review 17

2.1. Tracing history, development and current status of Artificial Intelligence 17

2.1.1. Definition and History 17

2.1.2. Artificial Intelligence applications: Understanding the conceptual background 19

2.1.3. Organisational decision-making: Decision theory and resulting challenges 21

2.1.4. Uncertainty and organisational decision-making 23

2.2. Artificial Intelligence programs: Challenges 27

2.2.1. SME's perspective 27

2.2.2. Impact of Artificial Intelligence on organisational structures 28

2.2.3. Challenges of using Artificial Intelligence in strategic organisational decision-making 29

2.2.4. Ethical perspectives on using Artificial Intelligence in strategic organisational decision-making 31

2.3. Artificial Intelligence decision-making processes 34
2.4. Theoretical Background 35
2.5. Real Experience and the Dark Side of Artificial Intelligence 44
2.6. Conclusion 48
Chapter 3: Research Methodology 50
3.1. Introduction 50
3.2. Aspect of research 50
3.3. Research Philosophy 51
3.4. Research Approach 53
3.5. Research Choices 54
3.6. Research Strategy 57
3.7. Data collection method 59
3.8. Sampling method 61
3.9. Data analysis 61
3.10. Ethical considerations 62
3.11. Conclusive remarks 63
Chapter 4: Discussion and Data Analysis 64
4.1. Literature Review Findings and Discussion 64
4.2. Data Analysis (Primary Research Data) 71
4.2.1 Survey Analysis 72
4.3. Descriptive Statistics 80
Chapter 5: Conclusion and Recommendations 89
5.1. Conclusion 89
5.2. Recommendations 90
5.3. Limitations of the Study 92

5.4. Managerial Contribution 92

Bibliography 93

Appendices 105

Survey Questionnaire 105

Figure

Figure 1: Decision-making model AI 13

Figure 2: Continuum of rational behaviour 18

Figure 3: Framework of capturing AI applications related to the continuum of rational behaviour 20

Figure 4: The basic organisational decision-making process as the framework for the analysis. 23

Figure 5: The AI Canvas 26

Figure 6: The decision-making process 35

Figure 7: Dynamic decision making 36

Figure 8: Overview of patterns of decision-making 41

Figure 9: Specification of Gender 72

Figure 10: Specification of Age Groups 72

Figure 11: Specification of different profession 73

Figure 12: Representation of the use of Artificial Intelligence in decision making 73

Figure 13: Role of AI in the decision-making process 74

Figure 14: AI is smarter decision maker than humans 74

Figure 15: Need for Human decision-making 75

Figure 16: Challenges in maintaining strategic organisational decision making 75

Figure 17: Dynamic decision-making theory 76

Figure 18: Use of AI in growth and success 76

Figure 19: Impact of AI on the performance of employees and staff members 77

Figure 20: Challenges for AI developers and IT employees with the implication of AI 77

Figure 21: Interpretation of humans and technology in the decision-making process 78

Figure 22: Successful implementation of AI for engagement of employees 78

Figure 23: Soft skills play a vital role in incorporating AI into decision making 79

Figure 24: Determination of team performance issues 79

Figure 25: The role played by AI in speeding the decision-making process 82

Chapter 1: Introduction

1.1. Background

One of the most challenging stages in the managerial cycle is dynamic interaction in organisations related to decision-making. Regardless of the pioneers' or leaders' insightful abilities, knowledge, and experiences, there is always the possibility of making wrong decisions. There is no doubt that the enormous advancement recently in the field of artificial intelligence (AI), which has thus achieved a personal change in various fields and arenas, has significantly aided in working with and working on the nature of different managerial exercises in associations.

Companies come into existence directly from the decisions (Pereira and Vilà, 2016) that define and compromise their strategy, and those decisions also shape the companies themselves. Because of the direct or indirect consequences that decisions may have on stakeholders, strategic decision-making is a dynamic and complicated process (Moreira and Tjahjono, 2016). Companies operate in complex contexts, and decisions may directly or indirectly affect interested parties (Carbone et al., 2019).

Decision theory has been around for a while and distinguishes between decisions that are made when some risks and decisions are made when there is ambiguity involved. In the first category, all potential outcomes, together with the odds that they will take place, are known and may be obtained through statistics or empirical research (Sydow, 2017). Nevertheless, the degree of uncertainty and the kind of uncertainty are both impacted by various factors concerning strategic organisational choices, which pertain to the latter group (Rousseau, 2018). Complexity necessitates that adaptive decisions be made to address it, supported by creating hierarchy and organisations to define roles. While this enhances the speed and efficiency of decision-making for operational decisions, it has been discovered that the quality of strategic judgments may be improved by adding a variety of viewpoints, experiences, and knowledge from a broader range of people (Rousseau, 2018). Therefore, organisations delegate the responsibility of addressing complexity while guaranteeing diversity to managers working in various areas (Rousseau, 2018). Strategic organisational decision-making is characterised in this study as group decision-making under ambiguity since consensus must be obtained among this group before a choice can be made.

Despite this, the capacity of humans to digest information remains constrained, even when more individuals are engaged (Fiori, 2011). Therefore, human decision-makers actively develop simpler models which deal with complicated situations sequentially to make them manageable for human processing capability. These models are called heuristics and rules of thumb (Fiori, 2011). This phenomenon is referred to as bounded rationality, and since Herbert Simon first articulated it in the 1950s, several academics have provided their unique interpretations of the notion. It is frequently considered an unconscious process that cannot be controlled (Kahneman, 2003), and it is also occasionally referred to as intuition. However, at the same time, it is argued by Simon (1995) that even intuition rests on a foundation of learned and experienced skills. This is the information and experience that the decision-maker chooses to rely on when calculating potential outcomes and probabilities, although it does so subconsciously. Therefore, the continuum between planned rationality and intuition is believed to be based on the agent's information-processing capacities, the task's complexity, and many environmental features (Fiori, 2011).

On the other hand, logical behaviour is subject to rules, which means that it must always be confined within a predetermined range of acceptable limits (Fiori, 2011). The human brain and computers are "physical symbol systems" that process information. Because of this similarity, the two are often compared.

In contrast to conventional mathematical theorems, computers are considered to be examples of AI, which Simon (1995) defines as mathematical and physical applications that can deal with complexity. Nevertheless, perspectives and research on the extent to which AI may be employed for the same activities as the human brain, particularly in decision-making, have been rare and varied in emphasis, technology or objective (Nguyen et al., 2018; Wright and Schultz, 2018).

Incorporating technology into business is not a recent innovation, as machines have been used in production processes to help humans for ages. However, machines are more of a tool, entirely directed by humans, and less defined in actual social cooperation situations than organisations are (Boone et al., 2019). AI is expected to allow computers to behave and react to human beings, suggesting that the connection between people and robots may shift (Huang and Rust, 2018). On the other hand, opportunities and risks have not been decided upon nor studied in more detail, making the study essential (Vaccaro and Waldo, 2019).

A review on financial institutions led by Dua (2019) explains that the clever data framework that relies on AI would give associations' chiefs more data that assists them with diminishing vulnerability about the choice. This improved banking administrations' quality, giving them an advantage and better execution. Haleem (2019) said that AI has a role in raising the efficiency of an organic performance by employing AI to make better and more accurate decisions to achieve the organisation's goals. Rathi (2018) referenced that AI has become exceptionally famous now and expressed that it is a blend of a few advancements and is the science and designing of intelligent machine production. Dwivedi (2021) explained AI methods saying that they are those strategies worried about making personal computer frameworks dependent on re-enacting which people use their faculties, knowledge and capacities to achieve the undertakings that the human psyche could achieve.

1.1.1. Artificial Intelligence Decision-Making

A contemporary company cannot function without its data since it enables the company to improve its decision-making processes and get a deeper understanding of its clientele. Nevertheless, this abundance of information brings a challenge: how can human brains possibly digest all of it? Here is where the decision-making capabilities of artificial intelligence (AI) play a part. AI decision-making is the process by which businesses incorporate AI into their operations to assist them in making quicker, more accurate, and more consistent choices using AI datasets. In contrast to humans, AI can do an error-free analysis of massive datasets in seconds, freeing up the team to concentrate on other tasks. Sixty-six per cent of those in decision-making positions believe that applications of AI, such as machine learning, computer vision, and natural language processing, are presently assisting them in increasing their earnings and achieving their objectives (Mckinsey, 2021).

AI decision-making is when data processing, such as identifying patterns and recommending courses of action, is done either in part or by an AI platform instead of a person. Allowing for more accurate predictions and decisions based on the data. In principle, if data is sent over to an AI platform, it should be possible for AI to complete activities such as data crunching, trend spotting, anomaly identification, and complicated analysis (Taylor, 2021):

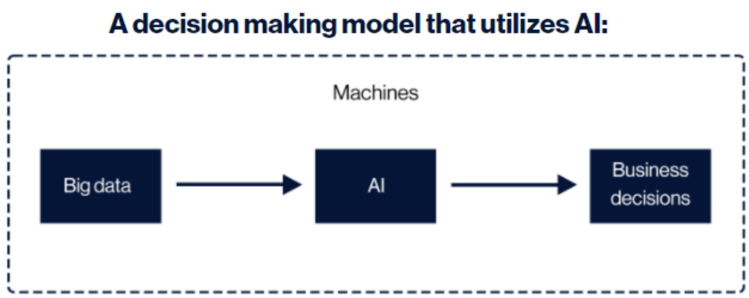


Figure 1: Decision-making model AI

(Source: Taylor, 2021)

The process is much simplified when judgments are made in this manner; nevertheless, it eliminates the involvement of people entirely, which is not always a good idea. Because of this, methods that integrate humans and AI are now getting much attention.

Therefore, it would be an understatement to argue that the use of AI for decision-making might be revolutionary for enterprises. McKinsey forecasts that by the year 2030, around 70 per cent of organisations will be utilising at least one form of AI technology, and almost half of all big enterprises will have a complete spectrum of AI technology incorporated in their operations (Taylor, 2021). AI decision-making has the potential to raise economic production worldwide, and the estimations are enormous: a theoretical boost of roughly $13 trillion to the world economy by the year 2030, which is an additional 1.2 per cent of global GDP (Garnter, 2019). It is anticipated that incorporating AI into corporate operations will be more crucial to companies than rising profits and sales. According to Gartner, companies are now being digitally disrupted by the sheer volume of data required to deal with, which might be overwhelming for them. However, with the assistance of AI, it is feasible to transform all of that data into actual consequences, beginning with sales and marketing and continuing through demand forecasting and supply chain management (Gartner, 2019).

1.1.2. Artificial Intelligence help in decision-making

One of the reasons why artificial intelligence (AI) is so helpful to business is that the more data-driven decisions an AI system makes, the more it can learn from those decisions and become increasingly valuable for organisations. AI helps organisations use collected data to construct models, which, over time, become highly proficient at generating forecasts and classifications based on the data feeds. The same models may be used to create predictions, categorisations, and recommendations when applied to live data in real time. This enables enterprises to make excellent business decisions. It seems like it would be a no-brainer to include AI in the decision-making process of a company:

- AI enables firms to make more informed decisions: Businesses can make quick choices because of the rapid analysis of massive datasets, such as what content they should develop for their target audience or what aspects of a failing advertising campaign they need to improve. It would take an inordinate amount of time for a person to do this, but a machine could do it instantly (Taylor, 2021).
- It may be beneficial to both marketing and sales efforts: AI applications, e.g., Natural Language Processing, assist businesses in better understanding how their clients engage with their brand, including the phrases they employ and the tone they should adopt to make their products more appealing.
- It enables companies to have a deeper understanding of their customers: Chatbots, algorithms, and machine learning are just a few examples of AI solutions that help organisations better understand their customers' needs, wants, and pleasures.
- It enables businesses to make judgments reflective of vast volumes of complex data: uniquely positioned AI will help make sense of enormous volumes of data, particularly in

situations where the effect can be precisely measured. AI can look at this data, but humans do not.

The issue is that even if decision-makers tend to have faith in AI, it is not always simple to win over their teams to the concept of AI and reassure them that it will not replace them in their employment anytime soon. According to several studies, this issue may have its roots in a lack of knowledge and cultural disparities on the degree to which AI may be helpful. Sixty-four per cent of those in charge of making decisions said that their teams do not trust or comprehend AI-enabled advice, making it difficult for their organisations to fully benefit from the technology (Taylor, 2021).

However, it is essential to comprehend that one need not see the situation in such a black-and-white fashion. It is not a question of determining whether computers or humans will make every choice in a corporation; instead, it is a question of weighing the pros and cons of each option. Both robots and humans have their advantages and disadvantages.

AI excels at overcoming obstacles such as noise and complexity, analysing large data sets, and recognising patterns almost immediately. However, people are excellent at comprehending a variety of external influences and coming to more creatively driven conclusions. The majority of problems can be solved most effectively by combining efforts from people and AI.

1.2. Research Problem

The rise of numerous advanced innovations for data frameworks, most notably artificial intelligence (AI) methods, has resulted in rapid mechanical turns of events and revolutionary changes in the new years. Berryhill (2019) demonstrated that AI had become a critical topic in association administration because it enables collaboration between association staff and AI to develop the emotional cycle further. Based on the organisation's prosperity and objectives, organisations utilise AI in dynamic cycles to maximise their capacity to examine data and deconstruct issues to concoct the best and most precise choices.

1.3. Research Questions

- What is the significance of artificial intelligence in the process of decision-making?
- In what ways the organisational design can assist in the decision-making process with the help of artificial intelligence?
- How can artificial intelligence become helpful in overcoming the challenges and issues faced by firms in the decision-making process?

1.4. Research Aims and Objectives

1.4.1. Research Aims

The main aim of the research is to find the significance of artificial intelligence (AI) tools in speeding up an organisation's decision-making process.

1.4.2. Research Objectives

- To analyse the effectiveness of AI programs in speeding up an organisation's decision-making
- To analyse if AI can make smarter decisions than humans or not.
- To analyse if AI can eliminate the need for human decision-making or not.

Chapter 2: Literature Review

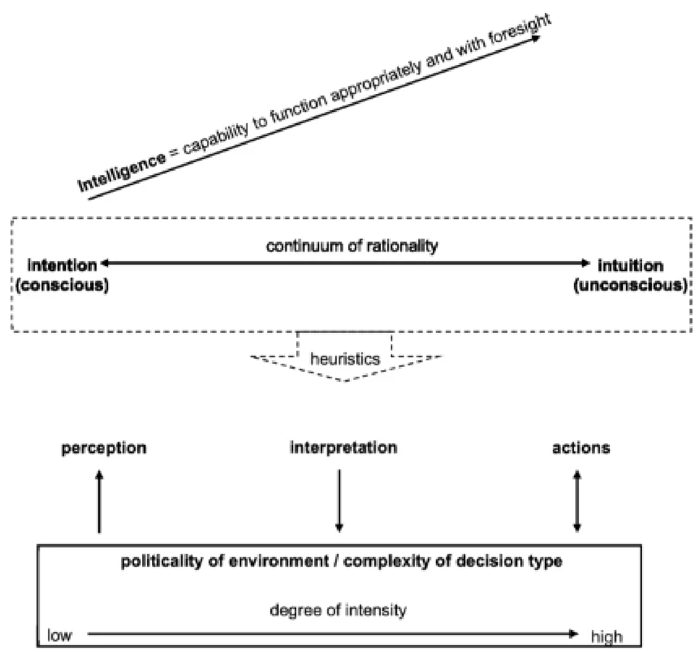
2.1. Tracing history, development and current status of Artificial Intelligence

2.1.1. Definition and History

In the sixth century BC, the notion of artificial intelligence (AI) developed when Homer depicted self-propelled chairs in the Iliad (Nilsson, 2010). Alan Turing, who built the computer in 1937, once said that AI would be achieved when a machine acted as intelligently as a person. The phrase "Artificial Intelligence" was initially used by McCarthy et al. (1955) in a plan for a Dartmouth summer research project to examine the extent to which computers can exercise intelligence. The team's mission was to provide a description of intelligence that would allow a computer to replicate it. In agreement with this point of view, Simon defines AI as “systems that demonstrated intelligence, either as pure research into the nature and function, explorations of the idea of human intelligence, or examinations of the processes that could execute practical tasks involving intelligence” (Simon, 1996).

Newer definitions emphasise the autonomy of machines, referring to “artefacts capable of carrying out tasks in the actual world without human involvement” (Huang et al., 2019) and “technologies that resemble human intellect” (Bolander, 2019). Similar methods could be used to broaden these definitions further; they all have the common thread of connecting intelligent machines to the human idea of intelligence, which is itself not established (Legg and Hutter, 2007).

This paper adopted Nilsson's (2010) definition since it is broad enough to include Simon's perspective and specific enough to serve as a road map for further investigation. To me, AI is the study of how to give computers the ability to learn and adapt to new situations. Intelligence is the trait that allows a human to act responsibly and imaginatively within its environment. A wide variety of skills, from observation to interpretation to creating actions to connect with, respond to, or even affect one's environment in pursuit of personal objectives, are required to "operate effectively and with foresight" (Bolander, 2019). The ability required is context and problem-specific. Decisions influenced by environmental factors, such as those in society and politics, as well as those within organisations, can be classified according to the framework outlined by Lawrence (1991). Considering that perception is more closely connected to intentional rationality, Figure 2 represents connecting these definitions to Simon's (1995) continuum of rational conduct. Interpreting and acting, however, necessitate the incorporation of new experiences and stored knowledge. According to Simon (1995), all processes are equally adaptable to human and mechanical execution. An algorithm is "a method or collection of requirements that must be met in problem-solving activities," which directly relates to this idea (Silva and Kenney, 2018). Algorithms, a fundamental component of AI, are analogous to humans' heuristic approaches.



The continuum of rational behavior (based on Simon 1986, 1995; Lawrence 1991; Nilsson 2010)

Figure 2: Continuum of rational behaviour

(Source: Lawrence, 1991)

However, there are drawbacks to this viewpoint. It is "morally impossible to enable it (sic) the machine to behave in all occurrences of life in the same way that the reason compels us to react," Descartes said in 1637, presenting one of the earliest examples. Bolander (2019) agrees with this point of view, saying that it is impossible to compare human and machine intelligence because of their inherent differences. Furthermore, there are varying opinions on AI's potential for creativity, emotions, or empathy. Other academics think AI is beneficial for specific sectors for which no abstractions, transfer of knowledge, or evaluation of unstructured activities are needed (Surden, 2019). Current research suggests that one must first comprehend AI's capabilities and potential harm to successfully incorporate it into organisational decision-making, particularly in comparison to or in contact with humans. This understanding should make it easier for people to adapt to new situations and lessen their anxiety about change. Morozov (2013) also stresses the difficulty of technical solutionism, the view that technology judgments are inherently better than those made by humans and the refusal to acknowledge the possibility of human error. Also included in this category is the potential for inadvertently or purposefully causing difficulties that could otherwise be solved with current technology (Morozov, 2014). Beginning with an examination of AI's scope of use, the following research sheds light on its potential and pitfalls.

2.1.2. Artificial Intelligence applications: Understanding the conceptual background

A precise description of an artificial intelligence (AI) programme is not yet available. Following Nilsson's description and the range of rational behaviour, Figure 3, categories of AI applications vary from less to more complicated depending on the context and the choice made (Nilsson, 2010).

Although Lawrence (1991) made connections between these factors and potential AI uses, he narrowed his attention to only two: natural language processing and expert systems. Since its first development, the range of benefits of AI has grown exponentially in almost 30 years. Therefore, following the lead of the vast majority of scholars, we shall classify the framework into bottom-up and top-down methods (Surden 2019). Implicitly-created programmes fall into the former group since they all statistically learn through experience and are not predictable, error-free, and understandable. Mathematical and statistical methods are part of the second category, although researchers do not recognise them (e.g., Haruvy et al., 2019).

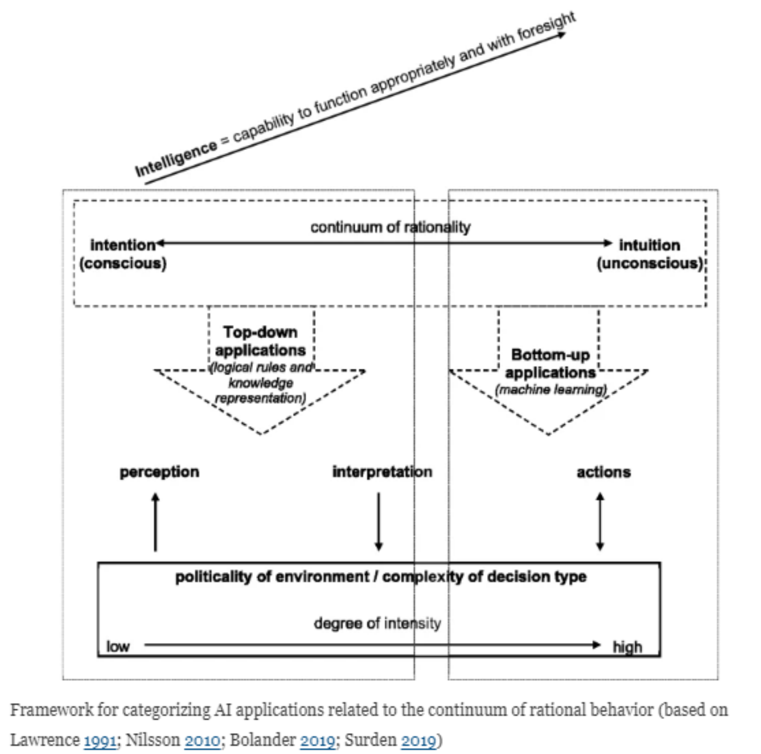


Figure 3: Framework of capturing AI applications related to the continuum of rational behaviour (Source: Lawrence, 1991)

Such programmes, also called logical rules or knowledge representation, were built on the rule's humans provide computers to automate specific tasks (Surden, 2019). This type of programme results in easily explained and predictable systems with well-defined skills (Bolander, 2019). Figure 3 provides a framework for connecting the categories to the spectrum of rational conduct, with top-down applications for observation and interpretation and bottom-up applications for acts, as this step necessitates the most knowledge. However, it is not feasible to define or agree upon specific applications for the categories because scholars cannot even agree upon existing mathematical applications, let alone decide upon novel applications for bottom-up AI. Most modern systems, especially those involved in making decisions, are centrally placed, "having a person in the loop" may contribute to this phenomenon (Bolander, 2019).

2.1.3. Organisational decision-making: Decision theory and resulting challenges

As was just discussed, making strategic judgments falls under the umbrella term of making decisions in the face of ambiguity. To select the optimal choice, we give each option a probability and a degree of utility, and then we pick the option with the highest total weighted value (Fredrickson, 1984). The probability levels are estimates and may be distinguished from one another by their coherence, conditionalisation, or convergence. The impact of frequency is related to the concept of coherence. A rise in the frequency of decisions comparable to those faced in similar situations leads to an increase in experience, influencing the estimate in a specific direction. The term "convergence" refers to the total number of participants. It is believed that the processing capacity will expand along with this number as it continues to rise (Resnik, 1987).

Utility levels are an individual's or group's expression of their subjective choice for several possible outcomes. Values cannot be defined in a way that considers all levels of utility equally, mainly when decisions affect or include many stakeholders (Liu et al., 2013; Melnyk et al., 2014; Wright and Schultz, 2018). Objectivity is only achievable to a limited degree where decision-makers are forced to rely even more on heuristics due to the uncertainty involved in information processing or group discussions in complex contexts. Additionally, the nature and degree of the reasoning behind a single decision might vary from one part of that decision to the other (Metzger and Spengler, 2019). Because of this, certain aspects of the decision may be impacted more intuitively than others exposing one to the possibility of being biased, resulting in erroneous issue definitions or an inaccurate assessment of the alternatives. After all, inevitable consequences are valued more highly than others or are influenced by assumptions like the sunk cost effects (Roth et al., 2015; Boone et al., 2019; Julmi, 2019; Kourouxous and Bauer, 2019). The beginning of false information at any point in the decision-making process by a single decision-making group can be considered conscious bias.

On the other hand, unconscious bias can result from an individual or group's lack of awareness of subjectivity, which can, in some instances, even significantly rise with expertise (Cheng and Foley, 2018). Research on decisions made under unclear circumstances has shown that groups decide more to follow the theory than individuals do or that groups can solve some of these obstacles through debate. Even though this is the procedure of decision theory relating to a single rational individual (Carbone et al., 2019), as a result of the fact that groups are also the primary focus of this investigation, the next part will give an outline of the most recent research (Kugler et al., 2012).

Decision-making in groups

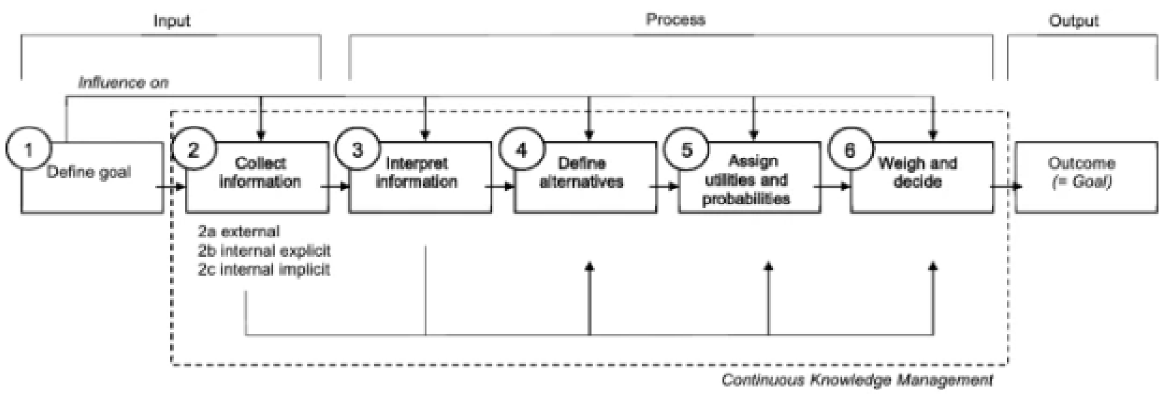
As was mentioned at the beginning of the study, for this article, the process of making strategic organisational decisions will be referred to as group decision-making under uncertainty because groups are the conventional form of organisation decision-making (Rousseau, 2018). It has been discovered that heterogeneous groups are better at making judgments than homogeneous ones. Information variety, discussion, or experience enhance interpretation, decreasing constrained rationality (Herden, 2019). Furthermore, it is not agreed upon whether or not groups assist in eliminating bias (Kouchaki et al., 2015) or whether or not they might also add it into a choice (Charness and Sutter, 2012). In addition, it has been discovered that groups participate in bargaining when assigning options and possibilities (Kugler et al., 2012). However, there is a lack of study on how groups define shared values (Samson et al., 2018).

As per Rousseau (2018), it is essential to look for various sorts and forms of information to improve the quality of decisions rather than relying on the most readily available information. Similarly, evaluating each source's credibility, accuracy, consistency, and applicability are essential. Researchers have discovered that utilising technology to collect and process data will have a supportive effect. While this could be facilitated if more people are engaged in the decision-making process, it could also be enabled when more individuals are involved in decision-making (Herden, 2019). Consequently, several researchers who study the process of group decision-making have called for further investigation into the use of group communication or information systems (Charness and Sutter, 2012). These researchers are particularly interested in computer programmes' role in assisting the organisation with decisions (Schwenk and Valacich, 1994).

Organisations must incorporate humans and technology in decision-making rather than involving more people to achieve significant improvements. As a point of reference for this research, the organisational decision-making process is broken down into parts in the following section.

2.1.4. Uncertainty and organisational decision-making

The procedure suggested in Figure 4 is founded on decision theory (Fredrickson, 1984) as well as various research on decision-making in the face of uncertainty that includes the participation of many individuals (El Sawy et al., 2017).



The basic organizational decision-making process as the framework for the analysis (based on studies from Fredrickson 1984, Beckmann and Haunschild 2002; El Sawy et al. 2017; Long 2017; Rousseau 2018)

Figure 4: The basic organisational decision-making process as the framework for the analysis (Source: Rousseau, 2018)

Initially, the decision aim is specified to serve as a benchmark for the rest of the procedure. Step two requires gathering knowledge that might be either external (from society, politics, law, or industry) or internal. Scholars classify privileged information as either explicit (such as facts and numbers about the firm, its goods, traffic flows, inventories, and pricing) or implicit (such as employee attitudes and motivations) (Rousseau, 2018). Since it involves highly personal characteristics, like emotions or experience, and is impacted by the level of trust or the motives for hidden goals that each group member has, implicit internal knowledge is more challenging to gather (Fu et al., 2017). The quality or credibility of the data produced from step two affects the subsequent steps since decision-makers must use the information at their disposal (Julmi 2019). Furthermore, the quantity of data processed is a factor, as most data collected is unnecessary, especially in large enterprises (Fiori, 2011). This framework's steps 2 and 3, referred to as "knowledge management", have a lasting effect on the rest of the process since information constantly flows (Long, 2017).

In step four, alternatives are identified based on the group's evaluation of the existing facts, influenced by the implication of internal and external factors on organisational culture. The fifth step is followed by aligning utilities and probabilities to that effect. The sixth phase involves discussing and settling on a final choice. The result would be equivalent to the intended purpose in a perfect world.

To simplify things, let us say that there are three parts to making a decision: gathering information, processing that information, and acting on what they have learned. Therefore, the framework is related to continuous space.

There is no consensus on the benefits of artificial intelligence (AI), and there has been no research to specify the phases at which AI can be helpful. AI applications execute a little decision-making process for themselves each time used, based on the aim employed and accessible data (Silva and Kenney, 2018), raising the possibility of bias in certain instances. Experts say it is unclear how the system comes to an outcome because there is no way to communicate with it (Bolander, 2019). However, the quality of an algorithm is limited by the quality of the data input and the quality of the programmed process mining, both of which are often performed by humans and are thus prone to bias (Barocas and Selbst, 2016). This is problematic because people cannot fix problems caused by flawed algorithms (Vaccaro and Waldo, 2019). On the other hand, researchers have discovered that some applications of AI can accommodate the problem of integrating ambiguous utility values (Metzger and Spengler, 2019).

AI has sparked a better data-driven decision-making strategy in business in several different directions. Retailers, for instance, often make dynamic price adjustments in reaction to data collected from customers' internet surfing habits and the preferences of the majority of their customers (Eukhost, 2018). For instance, it is common knowledge that some times of the day and throughout the week are better suited for purchasing flight tickets digitally (noon and in the middle of the week) and that there are also specific periods when costs are at their highest. The purpose of AI is to help with pricing, manufacturing, and product termination, and its role is to gather these details and link them together (Kephart and Walsh, 2004). In the same manner as AI, the terms "deep learning" and "machine learning" are gaining more and more traction to illustrate how AI programmes are getting smart enough to offer exact predictions or forecasts with very little probability of getting them wrong (Walters, 2021). The capacity of AI to interpret the future is directly correlated to its level of understanding of the past and its ability to conduct an in-depth analysis of prior experiences and occurrences. What gives AI machines or computers the capability to comprehend customers' preferences is the customers' previous responses and decisions. They are combined with differential algorithms designed to imitate the consumers and drive the decision-makers toward wise choices while simultaneously forwarding the customers intrinsically and extrinsically toward a particular product or service. This provides AI machines or computers with the opportunity to comprehend the preferences of customers. Since we are constantly linked to various intelligent gadgets such as phones and tablets, AI is already a significant component of our everyday life. However, feelings are not something that can be put into robots; human involvement is still the most crucial factor in circumstances in which abrupt and unexpected occurrences occur. Decisions that are attributed to human interaction are of the utmost significance, as they have the potential to earn any organisation an enormous reputation if they are made by public opinion and popularity. It is not appropriate for AI to be in charge of jobs that require the capacity to make appropriate trade-offs. This calls for a profound comprehension of the organisation's guiding principles, including its values, ethics, and aims (Walters, 2021).

The hiring process may be stressful and challenging for both large and small businesses. To discover the best candidate for the position, the hiring committee must look through the applicants' portfolios and consider each. However, the hiring teams review the applications and documentation the candidates have given throughout a normal recruiting process. AI's contributions to the candidate evaluation and selection process go beyond the application portfolio. AI will make it possible for HR to discover the candidates' social activities, allowing for a more thorough evaluation of their qualifications. Integrating the applicant's replies to intelligent applications or questionnaires can help restrict the contenders and concentrate the search on the applicants who are the best fit. AI can assist the HR department in reaching better applicants through innovative techniques. In addition, it is essential to point out that as a result of the continued benefits achieved by AI, it is estimated that AI will be able to replace 16 per cent of the jobs in HR during the next ten years (Sullivan, 2015). The University of Toronto's Rotman School of Management's Business School developed an AI Canvas intending to use it as a tool for making decisions. The seven parts that make up The Canvas are as follows: prediction, judgement, action, result, decision, training and feedback.

Figure 5: The AI Canvas

(Source: Ajay Agarwal et al., 2018)

The AI Canvas is utilised to probe and contrast customers' preferences concerning the value of return to cost. Intelligent machines can collect and process the data that is accessible, which assists humans in making better decisions (Forbes, 2018).

2.2. Artificial Intelligence programs: Challenges

2.2.1. SME’s perspective

Artificial intelligence (AI) may benefit young entrepreneurs and small businesses, allowing them to improve processes using cheaper technology and resources. Businesses can quickly obtain many email addresses for their customers to send them reminders, promotions, and even recommendations for products and services based on the study of their online browsing and purchase history (Mesir, 2019). For example, Mail Chimp business owners can synchronise the email lists of their offline and online consumers and establish segmented customer categories by separating clients into distinct groups according to their region, the frequency of their purchases, and several other factors. All these categorisations make it easier to distinguish which email is sent to which client.

By keeping track of the difficulties faced by each worker, AI can determine which individuals in the team have performance issues. For instance, if one of the workers is having trouble with a specific product or process, AI may submit this data so that the employee can receive appropriate training tailored specifically to this challenge. Through the use of specific software, AI can determine which members of the team are most successful in completing sales. After that, the supervisor will have the chance to investigate the member's performance and strategies. AI uses the available data, such as recorded conversations and emails, to accurately assess what language or behaviour assisted in closing sales with various consumers. This information may then be used to improve AI. Studies have shown that consistent training over time results in improved performance, which can keep sales managers busy even though they have a responsibility to teach the members of their teams. AI algorithms may support the training of employees in several different phases, including training members by imitating real-world experiences (Mesir, 2019).

2.2.2. Impact of Artificial Intelligence on organisational structures

According to von Krogh (2018), organisational structures are intimately tied to the decision-making processes because of the limitations of human processing capacity. However, this limitation may be overcome by spreading the responsibility for information processing or making decisions among roles and units with varying degrees of dependency. This conclusion gives credibility to the research conducted by Herbert Simon. This defining of roles and connections make information manageable, and all elements of the strategic decision-making process related to the aspect significantly impacted by the organisational strategy and associated goals (von Krogh, 2018).

It is also said that the motivations for an organisation to implement artificial intelligence (AI) depend on its strategy and aims (Bienhaus and Abubaker, 2018; Paschen et al., 2019). These are also suggested as a starting point for modifying or generating new structures that are anticipated to be essential for AI integration (Udell et al., 2019). On the other hand, von Krogh (2018) contends that the instant AI applications are employed, structures shift, affecting procedures and duties (Paschen et al. 2019).

Lismont et al. (2017) provide an alternative viewpoint by classifying businesses according to their level of preparedness to adopt new technologies. They conclude that a company's level of AI development correlates with the number of applications, the number of processes it has affected, and the number of objectives it has connected to AI. Consequently, Tabesh et al. (2019) suggest that the complex architecture of organisations should only be modified in increments while carefully adhering to the established strategy.

In conclusion, established organisational structures are essential to the smooth implementation of AI, and the latter is influenced by the prevalence of AI in the decision-making process. The variety and deployment of AI depend on the strategic goals behind its deployment. However, it is also anticipated that the available applications will impact the current decision-making procedures, which will require some modification to enable their use.

2.2.3. Challenges of using Artificial Intelligence in strategic organisational decision-making

It has been found that "not every strategic decision needs to be handled by technology" (Migliore and Chinta, 2017), making artificial intelligence (AI) literacy essential for deciding if, how, and why to incorporate AI into business operations (Kolbjrnsrud et al., 2017; Lepri et al., 2018; Canhoto and Clear, 2019). A significant issue is a lack of what Whittle et al. (2019) calls "AI literacy," a thorough familiarity with AI and its benefits and shortcomings. Scholars have argued that it is crucial to include employees directly impacted by AI integration in efforts to improve AI literacy rather than relying solely on upper management because acceptance of AI varies by hierarchy (Kolbjrnsrud et al., 2017; Bader et al., 2019). To establish their position, stakeholders must become tech-savvy and participate actively in the integration process. Furthermore, education and training are crucial activities (Watson, 2017), as evidenced by the literature. Several writers, including Migliore and Chinta (2017), and Whittle et al. (2019), stress the need to identify each person's skillsets to fully realise AI's benefits in the workplace. This also means that managers must provide their staff direction depending on their comfort level and expertise with new technologies (Whittle et al., 2019).

With the advent of AI in corporate decision-making, it has been stated that soft skills, such as the ability to work in a team, think creatively, and use good judgement, are more crucial than ever. It is best to ease into AI gradually since the confidence in the technology grows as people gain familiarity and proficiency with it. Employees learn to rely on it for work that has never been done by a machine previously (Lepri et al., 2018). When we talk about transparency, what we mean is "knowledge regarding the type and flow of data and the circumstances in which it is treated" (Singh et al., 2019) to arrive at an inevitable conclusion (Canhoto and Clear, 2019). Articles throughout this category often recommend forming an introduction team with a diverse set of members, including both beginners and professional members of the organisation's senior leadership and those with relevant experience and education (Watson, 2017). Scholars have argued again that leaders are responsible for assembling the best possible introduction team and giving guidance and encouragement during the introduction process. According to research by

Kolbjrnsrud et al. (2017), CEOs are more capable of understanding their role in guiding people throughout this process than middle managers.

Data security and privacy concerns, as well as the potential risk of data manipulation, are additional hurdles that the majority of scholars in this field have faced and which should be assessed before applying new technologies (L'Heureux et al., 2017). The articles take it for granted that this raises awareness and improves literacy, both of which work to reduce prejudice. More data is helpful, as discovered by Migliore and Chinta (2017). In contrast to the term used above, the writer of this paper characterises bias as a form of limited rationality. As a result, this premise is called into question, as collecting sufficient data of sufficient quality has proven to be a formidable task in and of itself. Bellamy et al. (2019) claim that “machine learning has always been full of statistical discrimination,” implying that even robots are prejudiced. Thus, AI Fairness 360 (Bellamy et al., 2019) and the Open Algorithms (Lepri et al., 2018) have been offered as frameworks that provide strategies for fair pre-processing, in-processing, and out-processing. Still, they are also criticised for allegedly just reducing bias. Additionally, Canhoto and Clear (2019) illustrate that decision quality ultimately depends on the application utilised, the resources accessible, the information supplied, and the interpretation abilities of the persons utilising it.

Thus, the evidence demonstrates that education and training, in combination with an understanding of data security risks, lead to literacy and openness, thereby reducing caveats. Furthermore, it has been observed that a successful implementation is achieved by focusing on the active engagement of impacted employees and a step-by-step introduction. Although the risk of active or implicit prejudice may not be reduced by these means, at least awareness is bolstered. Most scholars, however, have also argued that ethics and morality must be considered throughout the development of processes and structures.

2.2.4. Ethical perspectives on using Artificial Intelligence in strategic organisational decision-making

All academics in this field believe that an ethical framework is required before artificial intelligence (AI) may be used in business decisions. Still, they disagree on how this framework should be constructed. While some advocate for building decision rules in AI systems (Webb et al., 2019, Wong, 2019), others urge allowing the machine to discover ethical principles independently (Bogosian, 2017).

The concept of moral or socially correct behaviour, and the laws that emerge from it, are said to be very flexible (Cervantes et al., 2016; Giubilini and Savulescu, 2018). Since "what may be appropriate for one person may be utterly erroneous for the other," and "what may be proper for one legal framework might well be wholly incorrect for another," some scholars have suggested using a mix of legislative frameworks (Vamplew et al., 2018).

As Parisi (2019) puts it, "the challenge of automated cognition now concerns not just the capture of the social (and communal) elements of thinking, but refers to a general re-structuring of reason as a modern sociality of thinking," which in turn necessitates a greater perspective and definition of aspects like fairness, responsibility, moral blame, or guilt. Several scholars have examined human interactions with artificial agents to provide a new definition, focusing on how people attribute human qualities and flaws to computers. Webb et al.'s (2019) UnBias experiment proves that justice is the overarching principle in decision-making, even if individuals' conceptions of justice may vary. To guarantee equality, Wong (2019) provides a set of prerequisites. Just as crucial as having rules is ensuring everyone's voices are heard during decision-making. Other researchers have compared human-only, AI-only, and integrated decision-making contexts and discovered that moral culpability is permanently assigned to humans, regardless of context (Shank et al., 2019). According to Kirchkamp and Strobel's (2019) research, members of mixed-human-machine teams report a better sense of responsibility and a fall in selfish behaviour, but guilt remains stable. According to their research, robots are not yet credited with higher moral responsibility. Hertz and Wiese (2019) have discovered that consumers favour robots for analytical inquiries but prefer human counsellors for social and personal matters.

In conclusion, the question of ethics in AI papers is just as divisive as the topic of AI itself. According to Vamplew et al. (2018), "Legal and safety-based frameworks are best suited to the more limited AI which is anticipated to be created in the near to mid-term." This means that they are the only frameworks that can be agreed upon as a guideline (Wong, 2019). Thus, academics feel that incorporating ethical norms into algorithms is complex and always impacted by the individuals building them, even though various researchers have offered tools to facilitate this process (Cervantes et al., 2016). Some suggest that we need to rethink how we define social and moral standards in light of AI. Given the lack of a conclusive prescription for addressing this issue, Vamplew et al. (2018) propose a phased approach to determining what ethical principles should be upheld and how much leeway should be given to individual judgement.

The effects of artificial intelligence on the allocation of human and machine labour in large organisations

Industrial robotics, artificial intelligence (AI), and machine learning (ML) are all rapidly evolving technology, but their implications for the workforce and public policy have received little attention. New technology will displace many workers, positively impacting the availability and quality of goods and services. Workers who have been made redundant in an economy that employs fewer and fewer people will need to be compensated, as depicted by Kolbjrnsrud et al. (2017), Terziyan et al. (2018), von Krogh (2018), or Blasch et al. (2019), within their research.

There is already a noticeable influence on the economy from automation technology. Over the last few years, the number of industrial robots has exploded worldwide. Prices of robots, which can work continuously for long periods, are decreasing, making them cost-competitive with human labour. Computer algorithms in the service industry can carry out stock deals in a fraction of a second, considerably quicker than anyone could ever do. It is just a matter of time until these technologies find more and more use in the economy (Parry et al., 2016).

In the wake of the Great Recession, many firms were forced to operate with fewer employees, which increased automation. Following the increased commercial activity, many companies proceeded to automate their processes rather than hire more employees, mirroring a common occurrence among high-tech firms with a small workforce valued at enormous sums. If one compared the size of AT&T's employment in the 1960s to the size of Google's workforce in 2014, Google, valued at $370 billion, operated with just 55,000 people. The so-called "black-box dilemma" means that AIs increasingly rely on human expertise in the area to explain their behaviour to others who are not experts (Jarrahi, 2018).

It is hard to agree on how much influence automation will have on the labour market. Technology may lead to new job categories for those laid off, notwithstanding the dire predictions of others. Some claim that computers will have minimal influence on the workforce in the future. All policies dealing with the future of work must consider uncertainty in employment outcomes.

There must be a mechanism to give advantages outside of work if automation technologies such as robots and AI reduce job security in the future. Flexicurity is a concept for giving healthcare, education, and housing help to everyone, regardless of whether they have a regular job.

At the same time, Klumpp and Zijm (2019) assert that "activity accounts" might be used to pay for long-term schooling or charitable work. Fewer hours worked means more time spent with loved ones and artistic hobbies for others. What matters is that "people need to be able to live satisfying lives even if society only needs a relatively small number of workers."

At the same time, from the views of Agrawal et al. (2019), it has been demonstrated that various activities are regrading the human-machine interface that employees need to learn and can diversify their abilities (which includes how to use a chatbot to educate for better customer services). Despite this, only a tiny percentage of the businesses examined have begun to rethink their procedures to maximise collaborative intelligence. In any case, the takeaway here is simple: Organisations that deploy AI to replace human labour will miss out on the full potential of the technology. From the start, using this tactic is a bad idea. Conversely, future leaders will employ collaborative intelligence, altering their operations, markets, sectors, and workforces (Agarwal et al., 2019).

2.3. Artificial Intelligence decision-making processes

The vast majority of research conducted in this area concludes that "unique strengths of people and artificial intelligence (AI) can function synergistically" (Jarrahi, 2018). This finding suggests that, by combining the capabilities of humans and machines, productivity and profitability in decision-making are projected to increase (Shrestha et al., 2019). It is also widely believed that people and robots would be able to complement one another, which leads one to believe that AI systems might profit from human input (Jarrahi, 2018). This premise is supported by the work of other authors, such as Kolbjrnsrud et al. (2017), Terziyan et al. (2018), von Krogh (2018), and Blasch et al. (2019), which demonstrates the diversity of contexts in which the issue may be used.

Researchers have devised several models to establish how AI and humans should divide the work, ranging from giving all responsibilities to AI or hybrid systems to relying only on humans to make all choices (Shrestha et al., 2019). However, only Parry et al. (2016) and Agrawal et al. (2019) feel that it is conceivable to give AI the ability to make decisions independently without human intervention. On the other hand, they contend that this approach should not be used for all choices and that "the retention of a veto power where the decisions could have far-reaching repercussions for humans" is necessary for the circumstances like these (Parry et al., 2016). According to Bolton et al. (2018), AI may "automate tasks," which "allows humans to focus on activities that will bring value." Meanwhile, Klumpp and Zijm (2019) discuss the artificial divide, which means that humans become supervisors far more than executors due to AI. Individuals get more time to acquire talents that computers cannot mimic but are crucial for making smart strategic decisions due to the use of AI to automate certain portions of the decision-making process. According to the other authors, humans have significant advantages over other species in various domains, including judgement, analysis of political conditions, resistance to psychological influences, adaptability, inventiveness, foresight, and equivocation. According to the information presented by Jarrahi in the article, it has been depicted that even if robots are capable of producing the best alternative, they are less eager and competent to market it to a diverse range of stakeholders (Jarrahi, 2018).

The authors contend that AI not only has the potential to make robots more capable than humans but also can shift the role of humans into that of supervisors. The authors believe that only people possess the skills necessary to integrate these technologies into strategic organisational decision-making processes. As a result, the possibility of successfully integrating these technologies into such processes is minimal. Lyons et al. (2017) suggest that for the link between humans and machines to function, all participating parties should grasp the tasks, obligations, and duties and that a high level of transparency is required, similar to a human-only partnership structure.

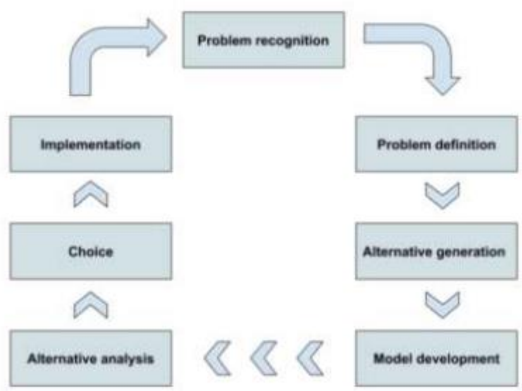


Figure 6: The decision-making process

(Source: Lyon et al., 2017)

2.4. Theoretical Background

Dynamic decision-making

The process of human decision-making is often dynamic, which means that experiences often inform what a person has had with previous decisions (Gonzalez et al., 2003) (Figure 7). The first phase of the decision-making process covers the preparation of the decision, which is the evaluation of alternatives. During this phase, the purpose for making a decision is selected, possibilities are sought by gathering data, and they are reviewed and rated. The second phase, known as "execution of choice," begins with selecting a particular course of action, followed by the actual implementation of the decisions. Phase three collects perceived feedback associated with the consequence of a choice, referred to as the assessment of the outcomes. The results of step 3 are then factored into other decision-making. We have chosen to organise all of the actions associated with a dynamic decision into three phases because we do not wish to comment on each functionality individually but instead provide the fundamental phases, which correspond to the period before, during, and after a decision is made. In order to compare the statistic decision-making, it has been depicted that it is an improved way of evaluating the outcomes to inform the evaluation of possibilities for subsequent decisions of a similar kind. However, in other words, it can be said that each decision is directly impacted by all those choices that were made in the past. On the other hand, static decision-making does not recur and is typically influenced by the lessons learned from previous (perhaps unrelated) decisions (Leyer, 2020).

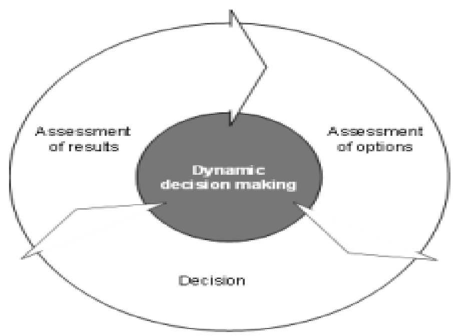


Figure 7: Dynamic decision making

(Source: Leyer, 2020)

These stages are typically vulnerable to human error since humans struggle to remember details accurately, do not have sufficient time or mental capacity to consider decisions, or have difficulty linking the execution of a decision and the feedback related to it (Leyer, and Schneider, 2021). As a result of these temporal and cognitive constraints, people frequently use a type of reasoning known as intuitive reasoning, which is characterised by being spontaneous, passionate, and occasionally prejudiced. On the other hand, analytical reasoning necessitates a careful and challenging process, but humans have a restricted capacity for remembering the past. Such thinking frequently necessitates time that is not readily available when one is faced with the necessity of making a decision. Artificial intelligence (AI) uses a form of thinking known as analytic reasoning. AI will always come to the same conclusion given the same set of circumstances since it is not affected by the circumstances or the emotions associated with those circumstances (unless programmed otherwise, e.g., by self-learning modes or unintentionally biased programmers).

Delegating decision-making to Artificial Intelligence

In light of the difficulties associated with making decisions in a changing environment, humans perceive benefits in outsourcing decision-making or sections of the processes to artificial intelligence (AI). Stone et al. (2020) discovered that there is no specific and commonly recognised definition of AI, even though AI is relevant in both research and application. They describe AI in their "100 Year Study on AI" as "a science and a collection of computing technologies that are motivated by—but often work somewhat differently from—the reasons that people observe, learn, reason, or take action.", an extensive definition of AI (Stone et al., 2020). In a more particular sense, Russel and Norvig (2016) develop four general kinds of AI interpretations: "thinking humanly," "acting humanly," "thinking rationally," and "acting rationally." In addition, the most recent research differentiates between "strong AI," which refers to the introduction of artificial intelligence (i.e., human-like) (Stone et al., 2020), and "weak AI," which focuses on AI-enabled processes by taking over vital work. In this work, we link to Stone et al. (2016) broad definition and 'weak' explanation of AI, where we focus on particular decision-making tasks regardless of whether they are executed in a 'human-like' approach. As a result, we incorporate various digital technologies with application scenarios, all of which extend over a spectrum of differing degrees of 'intelligence.'

The capacity of AI to learn from large amounts of data in a variety of forms and over a wide range of periods, as well as to derive inferences from this information, is the primary distinction between AI and traditional software (such as decision support systems) (Leonardi, 2020). Planning is not required to process these data; instead, it might develop over time via a process known as machine learning (ML), as AI examines the data that it has received as input (Leyer and Schneider, 2021). Based on this learning mechanism, software enabled with AI may construct its representation of a decision issue and offer its judgments on the optimal outcomes for achieving a predetermined objective (Maedche et al., 2019).

The affordances of AI are not brand-new concepts, but they are typically unavailable on the market as they require too much work from individuals or are hard to construct efficiently or cost-effectively (Townsend and Hun, 2019). AI oftAkki1109!!en acts on behalf of someone else, whether a human or a firm, who has entrusted it with a specific responsibility (Schneider and Leyer, 2019). Therefore, AI contends with the offerings given by humans and enables either a better execution or the creation of new proposals. These primary traits are what sets them apart from human implementation (Moore 2016): (1) infinite storage, (2) the ability to comprehend an enormous volume of information, (3) the cheap cost of acting 24/7, and (4) quick execution.

A shift in the sorts of service offerings that are offered as well as the interaction between clients and service providers, is brought about by AI as a result of its particular qualities (Leyer et al., 2020). For this purpose, many kinds of AI range from straightforward determinism to self-learning, through decision assistance to full delegations, from static to dynamic. In the context of AI, "dynamic AI" describes the practice of modified rules following their execution based on feedback or incorporating current information gleaned from the environment in which AI is functioning. As a result, AI can either supplement the decision-making process of humans or completely replace some stages of it.

Since we are interested in AI providing help for decision-making, we are using dynamic decision-making theory as a guide to design patterns of AI decision support. Therefore, AI can execute decision-making by taking over the evaluation of options (for example, judgement in the case of platforms providing standings of different offers), the choice to be carried out (for example, a navigation unit delivering the best route even without user interfering), and the evaluation of feedback for future decision-making. During the first phase, known as the assessment of choices, AI can witness humans' data or behaviour to assume the target of a potential decision, lookup for options (also specific keywords), identify alternatives (set criteria) or determined by data, as well as provide a ranking of decision alternatives based on these criteria. In addition, AI can search for options (also based on keywords provided). In the second step, known as a decision, AI may choose an option from the ranking based on the criteria that have been established and then automatically carry out the choice without any involvement from a human being. During the third phase, known as the assessment of results, AI can collect data on the repercussions of a decision from a device, monitor how the parameters identified for decision-making are influenced and use analytical models to provide findings on the effect of the decision.

Following the decision-making stages, delegation to AI can take place in one of two ways: either through an enhanced decision phase with AI or through an automated decision phase (Martin, Shilton, and Smith, 2019). If this is the case, the augmentation decision phase will entail some degree of partial delegation inside the phase itself, ultimately leading to humans and AI working together to carry out the phase, either be an interaction in the phase or a criterion defined beforehand by a person. During the phase of automated decision-making, AI is responsible for carrying out the entirety of the decision-making process.

AI requires at least some input to make decisions or carry out tasks successfully on humans' behalf. Data is essential, whether it be information on the amount of coffee still in the coffee machine or details regarding the vehicle's state and the necessary repairs. AI with more precise information would perform better than AI with fewer insights. As a result, businesses need to consider how they might gain unhindered access to their customers' actions, choices, and lifestyles. For instance, Google's Nest thermostat enables consumers to control their thermostats from a remote location and also creates valuable information from the connected home ecosystem, which Google then uses to serve its customers better. Another well-known illustration is Amazon, which closely monitors a customer's purchasing behaviour and uses that information to tailor product suggestions provided via the customer's personalised online account.

Patterns of decision-making processes with Artificial Intelligence involved

We adhere to the dynamic decision-making theory, which entails assessing many possibilities, making decisions, and then analysing the outcomes of that action. The phases that take place before a choice are described by the term "assessment of alternatives." During these phases, information is gathered on the decision, possibilities are assessed and discussed, and intentions are formulated. When a choice is finally put into action, this stage of the decision-making process is referred to as the "execution of the decision." As an illustration, when the acquisition of a product or service is carried out. During the feedback stage of the process, a post-decision evaluation of the results is carried out. This evaluation addresses questions such as "was the product or service excellent", "did it fit the customer requirement," and "did it perform well." All of the information gathered during the feedback phase may be used to inform subsequent delegation phases in the decision-making process before a purchasing decision is repeated or modified (Leyer, 2020).

In this day and age of artificial intelligence (AI), humans no longer need to play a crucial role in any of these three stages of the decision-making process (assessment, execution and feedback). In this study, we suggest seven patterns (evaluator, evaluator with hindsight, completely automated, informed outsourcing, executioner, learner, and deferrer) (Figure 8) of decision-making processes that incorporate AI. These patterns capture the several roles that a human or AI may play in presenting an evaluation of available alternatives, carrying out the decision, and providing feedback on the final result. Automation can take place in each pattern when AI is responsible for decision-making. In contrast, augmentation occurs when a human decides to give over all the automated executions to AI at any point during the distinct stages. The abstract nature of each pattern and accompanying instances of actual items or services are provided after each pattern's explanation below (Leyer, 2020).

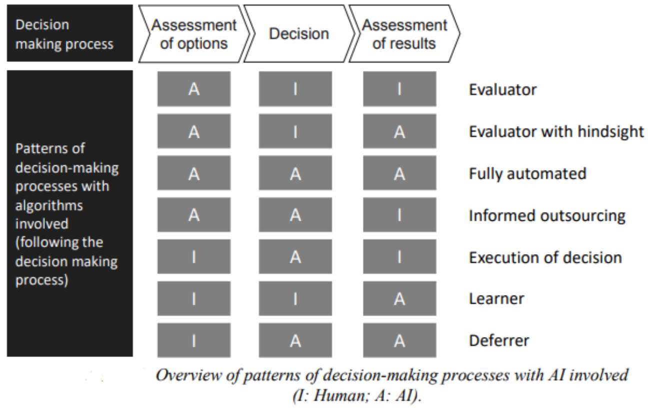


Figure 8: Overview of patterns of decision-making

(Source: Leyer, 2020)

Evaluator

Artificial intelligence (AI), when implemented according to this pattern, presents people with a collection of possibilities that are ordered according to one or more criteria previously supplied by the user (the decision-maker). To do this, AI has looked for available possibilities, evaluated them based on these parameters, and then evaluated them accordingly. In the event of automation, the person making a choice just needs to pick the most advantageous alternative. The analysis of the results is not provided in this report.

An online booking platform for flights is a good illustration of the evaluator pattern since it presents the best possibilities regarding flight time, price, and the number of stops on the dates and places the user has picked. When using AI to assist in decision-making, a human either gives AI a set of potential outcomes to consider or utilises the outcomes of AI to inform subsequent evaluations. In the given scenario, a human being would make use of the findings to conduct their search for other flight itineraries, which AI would not have thought to offer. When a person then uses AI again with the new knowledge to acquire better selections, this process might repeatedly continue (Leyer, 2020).

Evaluator with hindsight

In this approach, AI presents humans with a selection of possibilities that have previously been ranked based on one or more criteria. After the human makes a choice, AI analyses the results of the decision made by the human. In the initial phase of the process, AI has looked for available possibilities, evaluated them according to criteria, and carried out the ranking, from which the decision-maker must simply select the more beneficial option. After the human has made the decision, AI will follow the experiences of the human decision-maker with the chosen option where there is data available to alter the assessment criteria for the subsequent decision (Leyer, 2020).

Shoes suggested to a runner equipped with sensors that a digital watch can track to determine whether or not the shoes are adequately aligned to the runner's feet are an illustration of the evaluation pattern known as "evaluator with hindsight." The data can be utilised to propose when the shoes must be replaced, suggest a different shoe to be purchased the following time, or suggest exchanging the shoes within the first two weeks.

In the version with enhanced intelligence, a person either gives the first group of possibilities to AI, uses the information of an AI to undertake additional evaluations, or makes observations on the outcomes. The addition of evaluation step that has been discussed might consist of a person doing their observations based on the sensation of the shoe. These observations could either contribute to or differ from the outcome produced by AI. There is even the possibility of providing AI with human input on the reported findings of its assessment (Leyer, 2020).

Fully automated

In this scenario, artificial intelligence (AI) handles each stage of the decision-making process independently, without any human input. AI searches for available possibilities, evaluates those options, makes a decision, and then collects feedback for subsequent decisions. A completely automated pattern may be something like a dishwasher that uses sensors to determine when the container containing the detergent is about to be drained. After that, it determines when fresh detergent should be made accessible by computing the required quantity based on the predicted level of dirt, the available duration and intensity of the cleaning procedure, and the amount of detergent that has already been utilised. After gaining these insights, AI searches for detergent offers on trading platforms, making selections and placing orders according to the actual consumption efficiency experienced. After the human has manually supplied the detergent to the dishwasher, the consumption efficiency is estimated based on the amount of detergent necessary for the cleaning activities. This calculation then influences future decision-making throughout the order process (Duan, Edwards, and Dwivedi, 2019).

As was said, the enhanced version necessitates a person's involvement in establishing the decision criteria, with AI operating autonomously following the criteria specified. The same is accurate for evaluating one's available alternatives in addition to evaluating one's results, given that the human may supply guiding criteria for each of these tasks. As a result, there is not continuous interaction between AI and humans, and the decision criteria are initially defined and reviewed periodically. Nevertheless, humans are excluded from the current decision-making process, so they can automate it. In the case of the dishwasher, a person can set appropriate markets or product requirements (for instance, environmentally friendly items), restrict the maximum price, or offer feedback on how the appliance is being used (e.g., indicating upcoming holiday in the parameters suggesting increased demand) (Kuzior, Kwilinski, and Tkachenko, 2019).

Informed outsourcing

In this configuration, AI is responsible for searching for available possibilities, evaluating those options, and making the final decision. It is up to the human to offer feedback on the choices made to tell AI whether or not it was making intelligent decisions. The input is subsequently taken into consideration by AI when making decisions in the future. One use of the familiar outsourcing patterns is a music streaming service in which the user can override the song selections made by AI for subsequent playlists. After that, AI will keep away from songs with similar sounds.

The decision-making process for this pattern is handed over to AI by a human in the enhanced version of this pattern. In addition, if a human being chooses to ignore a choice that AI made, this may be accommodated through evaluating the outcome and formulating an alternative plan for the future. In the context of streaming music, a person can avoid hearing particular types of music without being forced to do so (Leyer, 2020).

Execution of decision

AI carries out the choice in this design pattern. After a person has looked for all available possibilities and evaluated them according to specific decision criteria, the decision is then made by AI. The human being modifies the choice criteria for future decision-making based on their feedback evaluation (Makridakis, 2017). The automatic purchase of shares in an online banking setting illustrates how the decision pattern may be implemented. The human being has settled on a specific thing and determined the cost at which that product should be purchased. AI will handle the buying independently when anything is accessible in the required quantity and at the defined price. AI can do this by continually watching the stock market, whereas a person would not be required to do so. As was said before, the enhanced form of this pattern refers to humans supplying decision criteria for AI to consider when concluding, avoiding particular trading platforms or stock categories in purchasing stocks (Leyer, 2020).

2.5. Real Experience and the Dark Side of Artificial Intelligence

It is now widely known that reviews and comments from company owners on artificial intelligence (AI) and how it contributes to the growth of firms have already spread extensively, which has led to an increased public awareness of the significance of AI in business. The most consistent theme from these evaluations is that AI may reduce wasted time while raising overall productivity. However, a discussion between two expert entrepreneurs (Elon Musk and Mark Zuckerberg) over the extent to which we require AI and the extent to which we should rely on it became viral. When going over the primary drawbacks of AI, it is essential to keep in mind that the development of innovative AI requires a significant amount of funding to construct the intricate hardware and software necessary to do specific tasks. As a result, it is anticipated that the maintenance cost will also be expensive, and there will be a restricted number of providers. Updating a unique and uncommon system can be troublesome and expensive for firms, especially if the system is novel and distinctive. Also, regardless of how much AI develops, it still lacks emotions and moral standards, which causes it to be unable to function correctly when exposed to new environments. Changes do not allow AI to improve automatically, nor does the change respond in any way apart from what they are created for (Mesir, 2019).

For its remarkable capacity for learning, AI has quickly become the dominant force in the commercial world. Better learning may be achieved through increased use of data-driven decision-making. AI can teach itself to construct models based on data sets. These models have the potential to make appropriate judgements and categorisations based on the data presented. In a related manner, the models provide predictions, classifications, and recommendations based on data promptly processed, allowing for more informed business decisions. Well-known firms such as Amazon use transactional data of their customers. By using this strategy, businesses can gain a deeper understanding of the subset of consumers that purchase similar items together.

Additionally, complementary items may be recommended on the websites with the aid of this approach. It enables websites to deliver improved suggestions to customers, which can lead to an increase in sales. Humans have been at the centre of decision-making until now, examining the data to determine which consumers should be targeted or what costs should be borne by a product launch. In addition, marketing initiatives presented an unacceptable level of danger in this context (Barber, 2021).

The development of AI is going to be crucial in the years to come. It is the bedrock upon which computer training is built. Computers have the capability of using large volumes of data thanks to AI. In addition, unlike humans, trained intelligence might potentially arrive at the best conclusions in a concise amount of time. Today, AI is increasingly becoming accountable for everything, including recent medical advances in the study of cancer as well as new studies on climate change.

Artificial Intelligence and Business Decision

Executives relied on inconsistent and incomplete data before the emergence of artificial intelligence (AI) and the commercial application of its principles. The advent of AI ushered in a new era of data-driven modelling and simulation. AI system of today starts from zero and is fed with a diet consisting of regular extensive data.

In the end, the application of augmented intelligence in business settings presents executives with game-changing models that may serve as the foundation for their decision-making processes. Multiple applications of AI contribute to an improvement in this capacity for decision-making. The following are examples of some of them: AI uses both automated cognitive and physical tasks to complete its work. It enables individuals to make judgments that are both faster and more reliable. To put it more succinctly, it automates decision-making while allowing for some degree of human interaction (InData Labs, 2021).

AI improves automation and minimises the labour and repetition required by human involvement. Consider the example of accurate weather forecasting. It is already common knowledge that AI-powered jobs may bridge the gap between climate scientists and data scientists.

Companies have improved their odds of surviving catastrophic events due to the implementation of AI decision-making algorithms in their operations. On the positive side, people worldwide have observed AI's game-changing effects on people and the economy. Now functioning as a hybrid kind of capital, AI contributes to expanding the economy and the human population.

Research commissioned by The McKinsey Global Institute estimates an additional 13 trillion dollars of output would be delivered by the year 2030 and anticipated that this would provide an increase of 1.2 per cent per year to the GDP of the entire world. In addition to the findings of other studies, this one believes that AI will have a revolutionary effect on how humans make decisions (Mckinsey, 2018).

Marketing Decisions

When it comes to making specific marketing decisions, businesses frequently confront several complications. More specifically, the complexities of customer-driven markets incorporating decision-making are growing daily. First and foremost, one must have an understanding of the wants and aspirations of the consumer. At some point, it will be necessary for the products to be in line with the crucial demands and wants. For effective long-term and short-term marketing decisions, it is necessary to have a strong understanding of the ever-changing behaviours of customers. People may be able to improve their understanding of the purchasers' perspectives with the use of suitable AI modelling and simulation tools. Techniques for rational decision-making using AI, such as decision support systems, could help improve one's ability to forecast how customers behave. The utilisation of this system makes it possible for AI systems to assist choices being made in real-time as well as updated gathering, forecasting, and analysis of market trends (InData Labs, 2021).

Customer relationship management

The process of managing client relationships has been vastly improved and made more flexible due to artificial intelligence (AI). It is capable of automating a variety of processes, including the recording of data, the maintenance of contacts, the analysis of data, and the evaluation of opportunities. Additionally, the buyer's persona model developed by AI can estimate the lifetime worth of a customer. These features make it easier and more effective for marketing teams to get their business done.

Automation efficiency

In corporate operations, the efficiency gained through AI-generated automation has surpassed that of manufacturing lines. Automated efficiency involves many aspects of running a business, including marketing and distribution, and AI has sped up several processes and supplied decision-makers with more reliable data. In marketing, individuals might obtain trustworthy insights about clients, improving contact with the consumer. The automated division of markets and administration of marketing campaigns have made effective decision-making possible (InData Labs, 2021).

2.6. Conclusion

Pay decisions range in complexity from setting a base salary for a position (the easier option) to awarding bonuses and promotions (far more difficult, more complicated and sometimes complex). In addition, the decisions that need to be made by leaders might be spaced out across several days or weeks. As a result, many pay choices fall under the decision support category, even though experiences and ongoing development may assure businesses to automate certain pay decisions for specific employees. According to a study by Gartner, one of every three companies is now using AI to make pay-related decisions. Seventy-nine per cent of those individuals report improved pay uniformity, and more than half believe it has improved their attempts to match pay for performance (Starita, 2021).

Data that has been acquired and processed appropriately has the potential to provide unmatched insights into any company. However, modern businesses struggle with being trapped in an ocean of data. The human force cannot keep up with collected data. It should not sound surprising that spreadsheets and database management systems are becoming obsolete. The question that arises now is whether or not people will be in charge or whether or not machines will take over decision-making based on data. Is it possible that AI may make better choices than humans? Is it possible for AI to make ethical judgments?

Humans are not capable of leveraging all the data

Relationships, new ideas, and recurring patterns are some examples of every component of a dataset compiled by human effort. They summarise the information to manage vast volumes of data. Processing millions or even billions of data is physically tricky for humans. The minds of humans are incapable of linking relations between data items, thought to be the core of any decision-making process.

Humans allow biases to take control over them

Essential data are given priority by humans rather than the information itself. Humans, in contrast to AI, linearly view data and, as a result, cannot process it in aggregates. In addition, AI can compile facts without allowing their emotional reactions to cloud their judgements and cause them to make mistakes. However, leaving all the jobs to robots is not prudent financially.

Human decision-making significantly impacts the decision-making process, whether it be an excellent piece of marketing content, an original marketing plan, or a choice to provide dedicated customer assistance. A decision-making model capable of passing inspection is jointly powered by human and artificial intelligence.

Chapter 3: Research Methodology

3.1. Introduction

The purpose of this chapter is to analyse the procedures followed to get the information in this report. Each method will be weighed against the research question and possible answers before making a final decision. By following the levels of Saunders' research onion, scholars may adopt a well-rounded approach to the issue. The method is like peeling an onion, with each layer exposing more and more information. Saunders' onion model study may be broken down into constituent parts, each corresponding to a distinct investigation phase (Akhtar, 2016). An organisation's success and achieving its goals are dependent on making the right decision at the right time. Unsurprisingly, many businesses are now employing AI in iterative cycles to make the most of the technology's strengths in analysing data and dissecting problems to arrive at the most optimal and practical solutions. Considering this, the researcher will conduct a comprehensive study by selecting appropriate research methods and ensuring a relevant conclusion from the study.

3.2. Aspect of research

Using scientific methods, researchers aim to find solutions to previously pondered problems. The primary goal of the research is to uncover the truth that has yet to be revealed. A research technique is a method for methodically resolving a research issue. It may be viewed as a science that studies how scientific research is carried out. We look at the many approaches researchers typically use to determine their research challenges and reasoning. When doing research, researchers must not only know how to construct specific indexes or tests; they must also know which techniques or approaches are helpful and which are not; what they imply and signal, and why they are significant. For this to work, researchers must be aware of the assumptions underpinning various approaches and the parameters by which they may judge whether specific approaches and processes are appropriate for a particular topic. The researcher must devise a methodology specific to their topic because no two problems are identical. Those that deal with the nature of things or the interrelationships among them are the two main categories of research questions. The researcher must first identify the problem he intends to investigate, i.e., the broad area of interest or facet of a topic he wishes to investigate. Once the problem has been defined, any ambiguities may be worked out to get to the bottom (Panneerselvam, 2014).

Before coming up with a solution, weighing the pros and disadvantages of several options is necessary. The first scientific investigation stage is identifying a specific study question. Forming a research question requires two steps: first, a thorough knowledge of the topic, followed by an analytical rephrasing of the problem. Discussing the issue with co-workers or others who know the subject is the most excellent way to grasp the issue better. In a university, a researcher might ask for guidance from a mentor, who is generally an experienced guy familiar with a wide range of research issues. To help researchers focus on specifics, many guides provide problems in broad terms that must be honed by the investigators themselves (Snyder, 2019). In the case of a problem in a corporate or government organisation, the administrative agencies are the ones that often identify it so that researchers may talk about how it arose and what factors are involved in solving it. Thus, in this case, the researcher has also decided to conduct a comprehensive study that helps analyse the measures to assess how AI can be used in intelligence programmes to speed up decision-making progress across organisations.

3.3. Research Philosophy

The philosophical foundations of research are as necessary as any other aspect of its methodology. Ontology, epistemology, and axiology are the sub-fields of philosophy that make up the field of research. These philosophical perspectives allow the researcher to take a viewpoint most effective for answering the topics. The researcher's viewpoint can be inferred from the assumptions outlined in their research philosophy, and these presumptions serve as the basis for this study's research design and methods. Academic inquiry provides a philosophical prism through which questions about the origin, development and ultimate value of knowledge may be investigated. Research philosophy is an underlying set of ideas about how knowledge should be obtained, processed, and applied. Researchers employ many methods to answer the research question, including primary and secondary data collection, statistical analysis, and in-depth interviews and surveys. The dissertation's research philosophy section is crucial for the researcher to reflect on and declare their most fundamental beliefs and motivations (Alase, 2017).

Concerns with reality, knowledge, and world values are at the heart of philosophy's primary focus in this broad field of inquiry. Philosophy's primary goal is to arrive at philosophical conclusions by employing a systematic, critical approach based on logical reasoning. Three primary schools of philosophical thought may be used to investigate the nature of reality, knowledge, and human values. To learn anything new, researchers conduct in-depth studies or scientific investigations. Findings from scientific research are used to address all research inquiries founded on the basic principles of philosophy. According to this definition, research philosophy is a way to describe one's opinions about what is being studied (Gupta and Gupta, 2022).

Choosing a research philosophy relies on the nature of the data being studied. As a result, the paradigm for scientific investigation comprises three parts: ontology, epistemology, and technique. The researcher's philosophical viewpoint and the studied social science phenomena should influence the methodological choice. However, the authors say more radical techniques might be restrictive when applied to scientific studies because of their philosophical implications. Intermediary philosophy is the only way for a researcher to reconcile research technique, philosophy, and the research question. Modern research methodologies are sometimes triangulated with traditional quantitative and qualitative approaches, which is frequent. Understanding the advantages and disadvantages of various approaches is critical, making it easier to plan the study and better grasp the subject under investigation. Unlike natural researchers, interpretivism philosophies are concerned with the activities of individuals rather than relying on the reliability of facts to derive 'rules' from them. This study is based on the interpretive method of research. Due to social researchers' dissatisfaction with positivism, an alternative approach called interpretivism was born. It aims to get a deeper grasp of how the study participants see the world through an empathetic comprehension of their perspective (Kumar, 2018).

For researchers, interpretivism is more than just a theory; it is a way of life. It is a philosophical approach that posits that individuals are separate from physical happenings because they make meanings. Interpretivism argues that social environments are too complicated to study, like physical phenomena (Armat et al., 2018). Research that takes an interpretive stance aims to shed light on the world from novel and nuanced angles. Therefore, to carry out a comprehensive study, the researcher will teach the interpretivism philosophy of research within the epistemological aspect to assess how AI can be used in intelligence programmes to speed up decision-making progress across organisations.

3.4. Research Approach

It is stated that inductive and deductive procedures are the two most prevalent research methods, with Saunders' onion as the underlying framework. Experimenting with hypotheses and updating theories are all aspects of deductive reasoning. It involves starting with a general hypothesis and working to more specific assumptions. A theory that has yet to be proved or disproved is the beginning point of this article; hence there may be some disagreement and various perspectives as to what the paper should or should not cover. Inductive reasoning is utilised when specific instances are used to conclude a general topic. This method relies heavily on empirical observation, and the research process begins with carefully examining the observed phenomena (Pandey and Pandey, 2021). The choice between an inductive and a deductive method to study is crucial. Researchers can carry out the entirety of the investigation by adopting a rational thought process. In the deductive approach, the researcher first reviews the existing literature and then formulates a hypothesis using the available evidence. Unlike deductive researchers, who extrapolate from particular, inductive researchers start with the big picture. Since no hypotheses will be tested in this study, the inductive methodology will be the most appropriate for accomplishing the stated goals and objectives. According to the inductive method, knowledge is obtained from secure observations to offer a basis for knowing and argue that reality encroaches on the senses; therefore, there is a direct correlation between sensory experiences and the subjects of those encounters. As a result, an inductive argument's conclusion offers to advance knowledge by extending beyond what can be learned from the premises. As the number of observations supporting the general statement grows, the likelihood of it increases. Generalisations can be verified by seeing specific examples that appear to support them.

In contrast, deductive reasoning begins with a specific observation, and inductive reasoning proceeds from there (Goundar, 2012). Assumptions are used with data to form a conclusion in inductive reasoning (Azungah, 2018). Hence, using an interpretivism approach combined with inductive techniques is the best combination that will aid the researcher in making sure that the study is in line with the use of proper and relevant techniques or methods in order to evaluate the elements of the aspect of how AI can be used in intelligence programmes for speeding up decision making progress across organisations.

3.5. Research Choices

Choosing a research subject and technique is the first step in the design of any study. These early judgments are based on preconceptions about the social environment, how research should be performed, and what genuine issues, remedies, and standards of "evidence" are. Theoretical and methodological diversity is reflected in many research methodologies, and it is generally agreed upon that quantitative and qualitative research are the two principal methodologies. Based on the principle, quantitative research investigates a specific issue by examining the data and analysing it using statistical methods. Quantitative approaches test whether a theory's predictions may be extrapolated to other situations (Mohajan, 2018).

In contrast, qualitative research aims to comprehend a social or human problem from different viewpoints. Qualitative research is undertaken in a natural context and involves the creation of a comprehensive and complete picture of the phenomena of interest through a series of questions and observations. For the best research technique, a specific study should be determined by the study's focus, the amount of funding available, the researcher's expertise, and the intended audience required to be deployed. Although quantitative and qualitative techniques may be employed in specific research, there are substantial distinctions between both approaches in their 'pure' form in terms of assumptions, data collecting, and analysis procedures (Patel and Patel, 2019).

Qualitative research collects, analyses, and interprets data based on what people do and speak. There is a difference between quantitative and qualitative research. Qualitative research focuses on meanings and concepts rather than numbers and measurements. As a qualitative researcher, one will conduct many more one-on-one interviews and focus groups on gathering data than one would in a quantitative research project. As a general rule, qualitative research provides in-depth information that is rich, thorough, and factually accurate. As a result, quantitative research may be used to identify causal links between variables in the population. Philosophical considerations must be taken into account when making this decision, e.g., how to proceed with the task at hand is dependent on the scope, the sort of data that must be collected, the context of the investigation, and the accessibility of available resources (time, money, and human). It is vital to remember that these are two distinct philosophies, not necessarily polar opponents. It is possible to combine parts of both approaches in a mixed-methods of study (Flick, 2015).

Measurement is the foundation of quantitative research. Quantitative phenomena can be described using this method. Comparatively, qualitative research focuses on qualitative phenomena, i.e. those that have to do with, or involve, quality or kind. It is critical in the behavioural sciences to conduct qualitative research to uncover the fundamental motivations that underlie our actions. Our findings can help us better understand what motivates individuals to act in a certain way or causes them to either like or detest a given product. Researchers used the qualitative technique to examine people's attitudes, beliefs, and behaviours from the subjects' perspectives. A researcher's thoughts and perceptions determine the course of their investigation in this circumstance. Projective interviewing methods, focus groups, and in-depth interviews are all often employed in this process. Experimentation or a survey are two methods for gathering primary data. During an experiment, the researcher observes specific quantitative measures, or data, to check the veracity of his hypothesis (Flick, 2015).

Accurate quantitative data, i.e., data obtained with care, analysed critically, and published, is reliable. Quantifiable data is limited since it does not give an in-depth account of how disasters affect the population—only knowing the number of individuals impacted and where does not give organisations and sectors enough information to plan for a disaster's response. It is possible to personalise a humanitarian response better if we know why and how an issue exists, the number of impacted people, and where they live. Community members might be asked to rate a prioritised list of requirements to get more quantitative data. However, this does not go far enough in describing why they are the most critical demands and how they are affected and impacted by local culture and values. There is much overlap between quantitative and qualitative data, but the procedures used to acquire each data type are distinct. Both data types are equally valuable, and neither is preferable. As a result, the most crucial step in establishing an accurate and comprehensive picture of the impact of a disaster on an impacted community is to guarantee that data gathering methods and data types are compatible. For accurate data, it is critical to ask the appropriate questions to the right people at the right time and in the correct context (Kuada, 2012).

As discussed above, the two most prevalent forms of doing research are the quantitative and qualitative approaches. Data are collected quantitatively and analysed with precision. There are experimental, interpretative, and simulated research methods included in this method. On the other hand, the qualitative method relies on an inherently subjective evaluation procedure. Findings in this study depend on the individual experiences and perspectives of the researcher. Typically, the types of outputs generated by this type of research cannot be subjected to rigorous quantitative analysis because of their non-quantitative nature. Methods of projection include in-depth interviews, focus groups, and others. Quantitative research tends to focus on observable and measurable aspects of a topic. The application of the behavioural sciences, which seek to identify the root causes of human behaviour, emphasises qualitative research.

Further, studies can be observational or cross-sectional, with the latter being the more common (Brannen, 2017). In cross-sectional research, both the result and the exposures are measured simultaneously. Because they rely on passive observation, cross-sectional studies are classified as descriptive rather than causal or relational research. Although this method helps describe existing community traits, it cannot be utilised to establish causal connections between variables. Inferences regarding potential links may be made, and preliminary data can be gathered to assist future studies and testing using this strategy (Kumar, 2018). Considering the aims and objectives of the research to conduct a survey, the researcher will use both quantitative and qualitative information to assess the use of AI within organisations. Thereby, based on the data collected, the study's conclusions will be drawn along with the use of the study's cross-sectional design (Feng et al., 2021). The research will benefit from incorporating the case studies of AI's actual application, as they will serve as both a valuable and trustworthy data source for the study's authors.

3.6. Research Strategy

The research strategy provides the overall direction of the research project, and the research methodology represents one of the components that involve the research process. It is essential to pick the correct research strategy based on study objectives, problems, available time and resources, the ideological foundations of the researcher, and current knowledge in a given domain. Diverse approaches to study exist, although they tend to converge in most cases. Due to this, it is critical to select the best appropriate approach for a specific research project (Awang, 2012).

Surveys are used to gather the information that researchers may utilise (from selecting samples to questions and topics). Using this strategy, many people may contribute their data, resulting in a wealth of helpful information. Respondents can be chosen based on various criteria, including gender, age, sexual orientation, socioeconomic class, or other demographics. In most surveys, these questions appear first. A researcher unsure about which focus groups on utilising may want this information (homogeneous or heterogeneous). Experimenting using the standard empirical technique involves thoroughly investigating the subject matter. Processes and phenomena are subjected to thorough testing in a controlled setting. Changing a single component of the test method is the primary goal of each experiment, while the other components stay static. In action research, a methodical approach to solving everyday problems is used to explore practical answers to such difficulties (Gupta and Gupta, 2022).

Research in this area aims to incorporate complicated dynamics into various social environments. It is possible to gather metrics that raise the efficiency and effectiveness of work in social organisations and agencies, human and health services, businesses, and educational institutions through a continuous cycle of structured study. With the help of this, people's well-being is improved, which in turn enhances social and professional activities. In industrial marketing, case studies are a common research technique. There is a possibility that this is due to the nature of the topic. One of the most well-known methods of qualitative research is grounded theory. Systematic data gathering and analysis are the cornerstones of this effort. Unlike other quantitative approaches, this one takes a unique approach to create theory, making it unique. According to grounded theory, there should be a continuous link between data collection and analysis. In addition to providing specified data analysis techniques, it makes it possible for outcomes to show up as rich and creative as possible (Goundar, 2012). Confidence may be guaranteed to researchers because of the vast data points they can utilise to support the study topic. Daily encounters drive qualitative social research, and ethnography prefers more subtle instances in this study. This form of observational research is known as a cross-sectional study. It is at this point that the researcher assesses the study participants' exposure and results, as well. Participants are chosen for research based on the inclusion and exclusion criteria. Following the task, the researcher evaluates the participants' exposure and findings. The prevalence of illness among clinical samples and the general population may be assessed using cross-sectional investigations (Mohajan, 2018).

When doing research, inductive methods are used to draw provisional conclusions about the distribution of, and patterns of interaction among, visible or measurable properties of persons and social processes. In research, an inductive approach is used to extrapolate from specifics. The focus of this type of research is on the development of theories that are grounded in the actual language, ideas, and experiences of people who participate in social interactions. This kind of study often begins with a detailed account of the appropriate behaviours and their meanings and then moves on to deriving pertinent typologies and concepts. In surveys to conduct research, scholars typically reach out to participants using online survey tools. Information gathered through surveys is evaluated statistically to help infer findings for studies. The purpose of a cross-sectional survey might be either descriptive or analytical. It is indeed fast, and it aids researchers in getting data in a hurry. When a descriptive examination of a topic is needed, researchers often resort to cross-sectional survey research (Gajjar, 2013).

Every company in the 21st century wants to know how their consumers feel about what they offer so that they may improve their offerings. Researchers have access to various tools and techniques, but surveys consistently rank among the most reliable and valid approaches. The purpose of an online survey is to get information from a specific individual or a group of people about a crucial issue in the business world. They are specifically designed to elicit meaningful responses from survey respondents. These companies may have access to a treasure trove of data with the help of credible survey research (Guha Thakurta and Chetty, 2015). Considering the aims and objectives of this research, the researcher will use a survey to assess how the use of artificial intelligence (AI) programmers helps speed up decision-making. Also, the same will be supported by case study inferences to ensure that comprehensive research is being carried out.

3.7. Data collection method

Research data collection begins with formulating a study topic and a research strategy and plan. Primary and secondary information should be considered when deciding on the data collection method for the research. The primary data are those collected for the first time and are consequently unique. On the other hand, secondary data have already been gathered and statistically processed by someone else. There are several ways in which the researcher might gather data for his study, and they will have to choose one or the other. There is a big difference between primary and secondary data collection methods because primary data must be gathered from scratch, whereas secondary data is merely compiled from other sources. Especially in the case of extensive inquiries, this data collection method is gaining popularity. The commercial sector, researchers, businesses, non-profits, and even governments embrace this technology. Postal questionnaires are given to the individuals in question with a request for them to respond and return them. One or more forms, each with a specific set of questions printed or typed, serve as the basis for a questionnaire. It is intended that responders would read the questions and jot down their answers in a designated section provided for this purpose inside each questionnaire (Patel and Patel, 2019).

On their own, each respondent must answer each question. Various economic and commercial surveys heavily rely on the data collection technique of distributing questionnaires to participants. A "pilot study" (Pilot Survey) is always recommended before using this method for testing questionnaires. With considerable investigation, the importance of a pilot survey cannot be overstated. The pilot survey serves as a practice run for the primary survey. When experts survey this, they can identify the strengths and weaknesses of the questionnaires and the methods used to conduct the survey themselves. It is possible to make progress in this area by learning from previous mistakes. Researchers must pay close attention to phrasing questions to get meaningful results. It is important to choose words carefully since they might have an impact on the answer. It is essential to use words that all respondents easily understand. Aim to steer clear of words having grey areas in their definitions. Any prejudice in the way the question is phrased should be avoided. Question formulation and wording are skills that can only be honed through repetition. Secondary data refers to data that has previously been gathered and analysed by someone else; hence, it refers to data that is already available. To obtain secondary data, a researcher has to look at a wide range of sources. Published or unpublished secondary data are acceptable sources of secondary information (Flick, 2015).

Considering the data collection method being primary and secondary, both these methods will be used in conjunction with the aim of the research to assess how the use of artificial intelligence helps speed up decision-making. The use of books, journals, blogs, and websites will be used as secondary data. At the same time, in the case of primary research, the information is collected using surveys, observation, and interviews. Herein, both methods are used as a case study of organisation examples and surveys are being represented for better comprehension of research (Kim et al., 2017).

3.8. Sampling method

Sampling methods can range from probability and non-probability sampling. Concerning the aims and objectives of this research, the most appropriate method of sampling is the random sampling method (probability sampling), wherein the researcher will select the participants based on the aim of the research (Ott and Longnecker, 2015). The participants in the study will be 50. The researcher will conduct the survey wherein these participants will be selected from the top organisations like Cisco Systems, Hyperlink InfoSystem, AKQA, iTechArt Group, DIGIS, Waracle and HData Systems, Softcat, and others that have been using AI for the decision-making process and whose case study instances will be represented in the research. The participants will be contacted through e-mail and seek prior consent for participating in the study by making them aware of the main aim of the research. This will help ensure that reliable and relevant opinions will help analyse results more effectively.

3.9. Data analysis

After the data is collected, the same is analysed concerning the aims and objectives of the research. The data will be analysed with the help of the descriptive statistical analysis method. The survey results will be analysed using SPSS (Statistical Package for the Social Sciences) tool to derive conclusions from the study. The results will be represented by describing every element by linking it with the case study instances. One or more datasets can be summarised using descriptive statistics, which give information on the properties and distribution of values.

Analysers can quickly see datasets' central tendency and degree of dispersion using conventional descriptive statistics. They are essential for determining how data is distributed and comparing different data sets (Flick, 2015). This will help provide deep insights into the subject matter of the study (O'Gorman et al., 2014).

3.10. Ethical considerations

The validity and trustworthiness of the data collected could be guaranteed because of the strict adherence to ethical standards. A person should never feel pressured to participate in a research study at any point in the process. Any method of persuasion or deceit aimed at gaining a person's confidence falls under this category. Participants must sign a permission form indicating their agreement to participate in the study and the comprehension of their rights to data access and withdrawal at any time. Consent may be viewed as an agreement between the researcher and their subjects. Confidentiality or anonymity of participants is essential, and promises extend beyond preserving their identities to avoid using self-identifying remarks and material. Participants need to be protected from damage by maintaining their anonymity and confidentiality. Two words that are often used interchangeably are participant anonymity and participant confidentiality. Conflicts of interest arising from the researcher's previous relationships or activities should be disclosed openly in an ethical approval application so that the committee may offer advice on how to handle them (Patel and Patel, 2019). An individual's explicit agreement must exist before they may engage in a scientific study. To reduce the possibility of unethical situations, researchers should apply data privacy considerations to the context of modern research. In addition, the records will be kept for five years, and the researcher will make sure that all interviewees and survey takers were given appropriate warnings and consented to have their data collected voluntarily to protect the integrity of the information and allow for an ethical assessment of the data and its depictions. Also, prior consent is required to be undertaken before moving forward with conducting a survey, and all the information will be kept confidential. Further, the researcher will provide creditworthy references to the scholars for referring to the secondary data (Wright et al., 2016).

3.11. Conclusive remarks

To conclude, the impact of AI on decision-making is another area that will be studied extensively in the future. Primary and secondary sources will be consulted for the data necessary for this inquiry. Primary data will be collected through the use of a survey. Moreover, data will be collected from secondary sources like scholarly publications, popular media, and the like. In addition, case studies showing how AI has been used will be brought in as references, adding credibility and practicality to the research process. A cross-sectional research design was selected for this study using quantitative data from a survey. Data from participants can be collected at a single moment in time using a cross-sectional study approach. This observational study style makes collecting participants' information more straightforward and practical. A descriptive statistics test will be run on the obtained data using SPSS, a statistical analysis programme.

Chapter 4: Discussion and Data Analysis

4.1. Literature Review Findings and Discussion

Considering the above discussion based upon the viewpoints of the researchers and investigators regarding the research topic, it has been found and analysed that artificial intelligence (AI) is the primary focus in corporate tech discussions. The potential of AI to evaluate data and draw conclusions that might inform crucial business choices is enormous. Organisations worldwide are exploring how to implement best this cutting-edge technology to maximise their development potential (Greenberg, 2020). Artificial intelligence's revolutionary potential as an organisation decision-making aid has reshaped the commercial landscape. Profitable ventures are being propelled forward primarily due to the use of AI and its integration with other applications.

In order to support this, the studies of Fountaine (2019) depicted and analysed that rapid progress in AI software has resulted in ground breaking advances in the area, enabling machines to handle and analyse data in ways we could never have predicted. More advances in AI are on the horizon as technology advances. In the future, AI will use both cognitive and physical tasks that can be mechanised. In turn, this improves people's decision-making speed and precision. The process automates decision-making with a small amount of human oversight. AI improves automation and lessens the need for human labour in routine activities. Companies may be able to save time and money by automating and optimising mundane procedures and activities with the help of the correct AI technology. Raise output and effectiveness of operations—speedier business choices with cognitive technology results (McCarthy et al., 2019). AI, unlike humans, can evaluate massive datasets in seconds with zero mistakes, allowing staff to focus on other tasks.

Decisions made by AI are implied with the effective use of AI within workplaces; businesses can use datasets to make timely and reliable choices or make the best decisions. In contrast to humans, AI can perform error-free mass analysis of data sets in seconds. The more data-driven judgments AI makes, the more it learns, which is why it is helpful for organisations. AI learns from its own experience and the data it collects to create models that become highly competent at generating inferences and organising this data. Businesses may benefit significantly from applying these models to real-time, streaming data for prediction, classification, and recommendation purposes.

At peak, for instance, analysing consumer transaction data gleaned from hundreds upon thousands of sales to determine what kinds of items particular groups of customers like to buy together. Complementary items are suggested on a website using this strategy, such as Amazon, to encourage repeat business from existing consumers (Alsheibani et al., 2019). Compared to how businesses were run a century, half a century, or even just two decades ago, this is a radical departure. Because before today, every significant choice had to be approved by a single person.

Humans, not algorithms, evaluated data to determine which clients to focus on, which marketing strategies to implement, and how much a new product launch would cost. Various academic investigations have pointed to a lack of familiarity with AI and cultural differences as possible causes of this issue. Sixty-four per cent of decision-makers think that the lack of confidence or understanding of AI-enabled advice makes it difficult for their business to benefit from the technology entirely. However, they should be aware that things are not always so simple. Both humans and robots have their place in commercial decision-making, and neither should be relied on exclusively. AI excels in sifting through large data sets in search of patterns, despite noise and complexity. However, humans excel at taking in information from the outside world and generating judgments based on our unique brand of creativity. Cooperation between AI and humans is often the most effective course of action. While AI may be able to gather and analyse data more quickly and readily than humans, it does not imply that doing so is necessarily a sound economic decision (Shrestha et al., 2019).

Human interaction is essential for every business to succeed. Whether via persuasive writing, risky advertising, or caring service to customers, there are countless methods for individuals to affect positive change in the world. This is how AI aids in corporate decision-making. Identifying client requirements and adapting goods to meet them is complex. Because of how crucial it is to the success of any given marketing strategy; organisations are actively seeking methods to foresee their customers' actions. Algorithms powered by AI examine customers' browser histories to conclude. The data from these analyses inform smart advertising choices for companies. Some examples include giving out product suggestions and tailored emails and conducting targeted marketing efforts to reach the right people at the right time.

For instance, both Spotify and Netflix utilise AI and ML (machine learning) algorithms to deliver content specifically curated for each user. Customers are looking for similar customised suggestions from other firms as they get accustomed to services like Netflix and Spotify. This is how AI makes it easier for businesses to make decisions. AI is reshaping the corporate landscape by increasing creativity, productivity, and the scope of business operations with the potential to revolutionise business goods, procedures, and judgments. Current tools should allow companies to achieve AI-powered organisational agility (Stone et al., 2020).

In order to contradict the above statement, it has been analysed from the studies of Yang (2019) that for AI to be effective in helping businesses achieve their objectives and expand, top executives must drive change and assess where and how complicated AI should be applied. The effects of AI may be seen in all marketplaces. Supply chain, transportation, education, operations, marketing, and almost every other industry is on the path to digitalisation, moving away from manual processes by integrating AI. With AI's support, businesses can better prepare for and respond to disasters using AI decision-making algorithms, spot abnormalities, and anticipate customer behaviour. AI improves automation and lessens the human effort and boredom required for forecasting and prediction analysis. Deloitte recently presented data that identified the top five advantages of using AI in an organisation: improving the current product, streamlining internal processes, streamlining external processes, releasing employees to be more creative, and assisting leaders in making better decisions (Yang et al., 2019).

Utilising AI to improve processes applies to nearly all businesses, but using AI to enhance products is unique to each company, depending on product core strength, industry, and customer participation. Automating routine internal tasks like scheduling, reminders, and follow-ups is now possible in project management thanks to AI technology. One of the many ingenious ways these technologies may help people save time is by preventing any omissions from occurring amidst their busy schedules. Managers and leaders are receiving assistance from AI-based solutions, which assist them in setting priorities and making sound decisions across the whole planning and execution process. It aids in processing project data and finding patterns that may affect project completion.

By 2030, AI is expected to replace human project managers in all but the most menial activities. Using variables such as project size, contract type, and project management ability, AI will soon be powering many operational tasks, from planning to data gathering to tracking and reporting. Automation will also enhance the process of requirement-based project sequencing. AI-driven automation and optimisation of project data sets will help businesses increase the return on their project investments while freeing up resources for new products and expansion.

Furthermore, there are always potential dangers lurking in each undertaking. AI can aid in early defect or redundancy prediction and overall risk analysis and mitigation. It is a valuable tool for managers since it allows them to estimate the time and resources needed to finish a project and avoid delays. For future projects, realistic timetables may be predicted using ML and AI by looking at previous data, such as anticipated start and finish dates (Ghosh et al., 2018). In the future, AI may be able to study humans and draw conclusions about their behaviour based on their observed patterns. AI systems may keep tabs on ongoing projects and the actions of team members, allowing them to detect patterns and nuances that humans would overlook.

On the other hand, when it comes to demonstrating the findings and analysis based on the factual statement, whether AI can make smarter decisions than humans or not, it has been found from the studies and viewpoints that in AI, both cognitive and physical labour are mechanised. Decisions can be made by people more quickly and accurately. To put it succinctly, it automates decision-making with some human oversight. AI improves automated processes, requiring less manual labour and eliminating tiresome chores. Nevertheless, there are situations where AI decision matrices can outperform those based on human judgement because of their superior pattern-finding capabilities, which allow them to quickly and accurately analyse massive data sets. However, AI has a minimal capacity for complicated divergent reasoning on its own. Therefore, this analysis and the research findings show that AI is not more intelligent than humans.

Once the stuff of science fiction, the idea of creating AI has moved from the screen into the realm of possibility. For a long time, people have tried imbuing machines with intelligence to make their jobs easier. In certain situations, bots, humanoids, robots, and digital people can perform as well as or better than humans. AI-powered applications are superior to humans in repetitive, tedious work because of their superior speed, accuracy, and operational competence.

On the other hand, Akerkar (2019) analysed that Human Intelligence (HI) is associated with the ability to learn and adapt to new situations. Data preparation steps, like those needed for AI, are not always necessary. Compared to the computer's hardware and software, a human's memory, computational capacity, and physique may seem trivial. Human minds, however, are considerably more multifaceted and profound than anything now achievable by technology.

Regarding the AI vs HI argument, current AI mimics human intelligence more precisely than previously; nonetheless, robots are still well beyond what human brains can achieve. Our capacity to use our knowledge through logic, reasoning, understanding, learning, and experience sets us apart as a species. As they say, "knowledge is power," and with that power comes immense duty (Akerkar, 2019). Machines may emulate human behaviour to some extent, but they may not be able to make sound, reasoned judgments. AI machines can make judgments based on patterns of events and their connections, but they have no "common sense". Machine learning algorithms have no concept of "cause" or "effect". Meanwhile, situations in the real world necessitate a person-centred, comprehensive approach.

Moving forward, it has been shown that AI experts and data scientists today are focused on approaches to overcome such catastrophes in creating the algorithms and boosting AI's capacity, indicating that there are distinct perspectives of the study regarding the emphasis of individuals associated. With reliable information, we may develop AI-based tools that can work in tandem with human values and productivity. As a matter of survival, we must build these AI devices with human-like intuitions, instincts, and reflexes (Riedl, 2019). Human elements such as accuracy, precision, timeliness, and quality judgments are essential and should be incorporated into AI input algorithms.

In contrast to AI, HI thrives on instruction and direction. Despite the current state of knowledge and our AI achievements, computers still struggle with language processing, vision, image processing, development, and common sense. Since AI is still maturing, its future depends on how well we regulate AI programmes to ensure they respect human values and adhere to security standards.

In contrast, research has found that AI's learning ability makes it the pinnacle of corporate success. An increase in the quality of data-driven judgments is comparable to enhanced learning. AI has the capacity to self-train in order to construct models from large datasets. When given sufficient data, these models may correctly classify it. Similarly, the models predict, classify, and suggest based on data in real-time. Better business choices may then be made as a result.

Retail giants like Amazon, for example, utilise information about customers' purchases to improve their services. This method helps businesses understand which customers frequently buy the same items. This model also aids in recommending related items for purchase on the respective websites. Websites may now enhance sales and improve suggestions for their customers. Humans have always been at the centre of decision-making (Asan et al., 2020). Humans examine data to determine which consumers to focus on or how much to budget for a product launch. Plus, promotional initiatives entailed too much danger under these conditions.

Moreover, it has been analysed that decision intelligence will not do away with the requirement for people in the decision-making loop, as evidenced by the findings of researchers and studies. Organisations nowadays have too much data. Since there is now more data than any single human being can ever process, traditional business intelligence tools like spreadsheets are no longer sufficient. However, adequately processed data may give decision-makers unique insight into every facet of an organisation. Decision Intelligence and AI can help them to put all that data to use in areas like sales, marketing, demand planning, and supply chains. We humans will always have limitations when making judgments based on evidence. However, in order to succeed, businesses always require human interaction. Killer commercial content, a daring and innovative advertising approach, or caring choices made in the name of customer service are just a few examples of how people may affect others' choices for the better (Jarrahi, 2018).

Recently, scholars have widened the topic to include the implementation and use of AI. AI has progressed with the advent of ML, and deep-learning algorithms, which help eliminate blunders and errors brought about by human judgement. For several reasons, AI algorithms are essentially distinct from other algorithmic technology. To start, AI enhances efficiency by learning from its own mistakes and gaining insights by analysing new data in light of its experience. AI's capacity to unearth concealed patterns makes it suitable for perceptive jobs requiring human-like "intuition". Second, given enough training sessions and large data sets, AI can provide accurate predictions and judgements (Zerilli et al., 2019). Third, with sufficient time and training, AI-powered models may eventually outperform those that do not. Because of these unique qualities, AI can compete with and surpass human creativity in some fields when it has only excelled at jobs involving repetition and recognition. High-level cognitive activities, such as making a legal judgement in court, identifying protein structure in biology, and playing strategic games, are where researchers have found AI to perform admirably.

Therefore, businesses have started relying on AI algorithms for jobs that need sound judgement, such as bettering the distribution of scarce resources, setting up work schedules, and assessing employee output. By way of illustration, AI algorithms are helpful in the creation of novel pharmaceuticals, especially in the preliminary stages when work in this area relies primarily on computerised data processing and pattern recognition (Lou and Wu, 2021). Hospital medical coders can also benefit from AI recommendations for chart coding. Given the idea of limited rationality, which states that people try to strike a balance between the time and mental energy it takes to make a good decision and the results it yields, it stands to reason that people will try to find the most efficient way to do so. AI has the potential to help reduce expenses, which would have a positive impact on the reliability of judgments (Xu, 2019). Put another way, AI aids human decision-making by assessing more possibilities at once and at a lower expense and evaluating those options more accurately. The decision-making processes of human experts may be reexamined with the help of AI since it can present many well-evaluated options that inform and instruct them (which may have yielded bad decisions if not trained with AI). Therefore, our fundamental expectation is that AI can teach human experts and improve the quality of their judgments, mainly when AI performance is superior to humans and jobs are complicated and unclear (Goralski and Tan, 2020).

Hence, fewer studies like Loh (2018) have looked at whether AI may enhance natural human talents in decision-making, even when AI technology is not physically present in the workplace. AI has helped people perform better in their jobs; assistants do not indicate that AI has helped develop essential human skills. While using a calculator can raise the user's speed and accuracy in calculations, it may also lead to the atrophy of the user's arithmetic skills (Loh, 2018). Therefore, it is crucial to separate AI's pedagogical functions from its ancillary ones. In this work, the author argues that AI's impact may extend beyond that of an assistant by educating human professionals to make better judgments.

4.2. Data Analysis (Primary Research Data)

In this section, the results analysed from the targeted participants and individuals are going to be represented here in an effective way. Accordingly, the collection or gathering of data will include the participants' contribution through e-mail and seek prior consent for participating in the study by making them aware of the main aim of the research. Ensuring that reliable and relevant opinions will help analyse results more effectively.

4.2.1 Survey Analysis

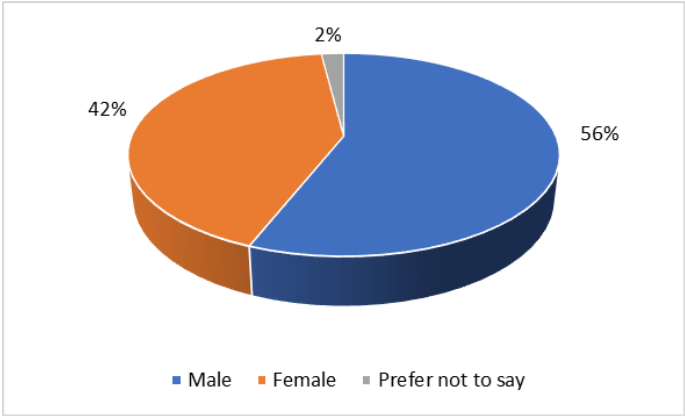


Figure 9: Specification of Gender

Of 50 responses received, 42% were male, 56% were female, and 2% preferred not to define their gender (Figure 9).

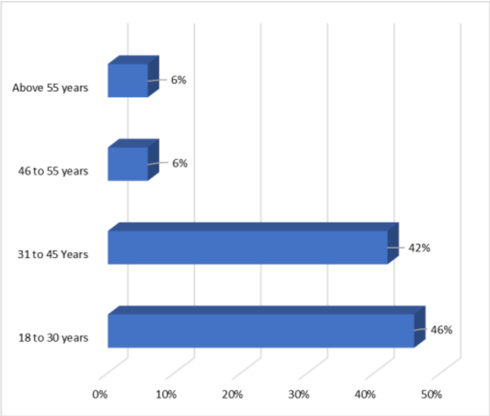


Figure 10: Specification of Age Groups

Most respondees are 18 to 30 years (46%) and 30 to 45 years (42%). 12% belong to the age group of above 45 years. (Figure 10)

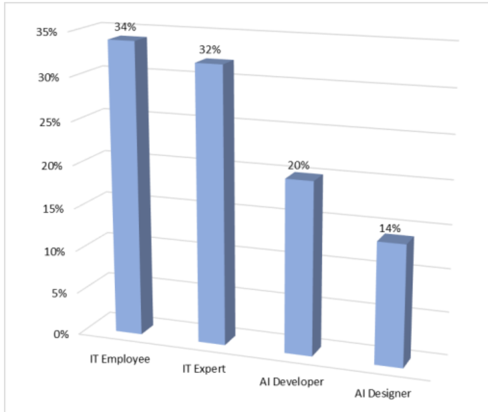


Figure 11: Specification of different profession

The majority who provided their opinion were IT Employees (34%), followed by IT Experts (32%), 20% are AI Developers, and 14% are AI Designers. (Figure 11)

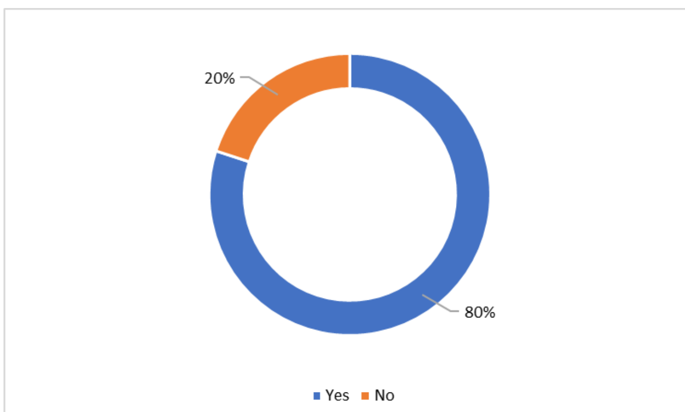


Figure 12: Representation of the use of Artificial Intelligence in decision making

When asked about the use of AI in decision-making, 80% of responders were aware of the use of AI in decision-making, whereas 20% were unaware of the concept or role of AI in decision-making. (Figure 12)

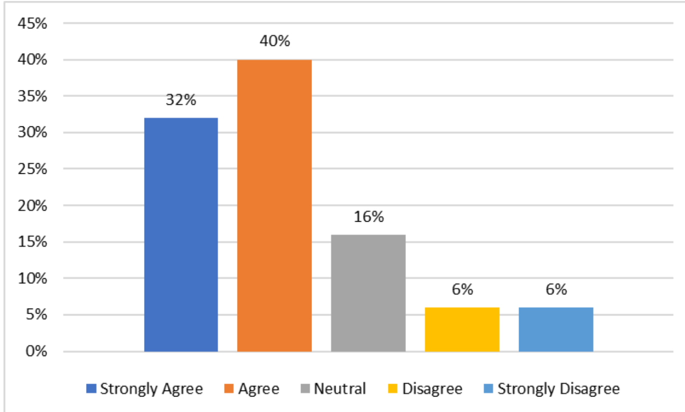


Figure 13: Role of AI in the decision-making process

The survey data shows that 32% strongly agreed that AI plays an essential role in speeding up the decision-making process. In addition, 40% also agreed with this statement. On the other hand, 12% disagreed that AI played an essential role in speeding up the decision-making process. The remaining 16% were not sure if AI plays an essential role or not in speeding up the decision-making process. (Figure 13)

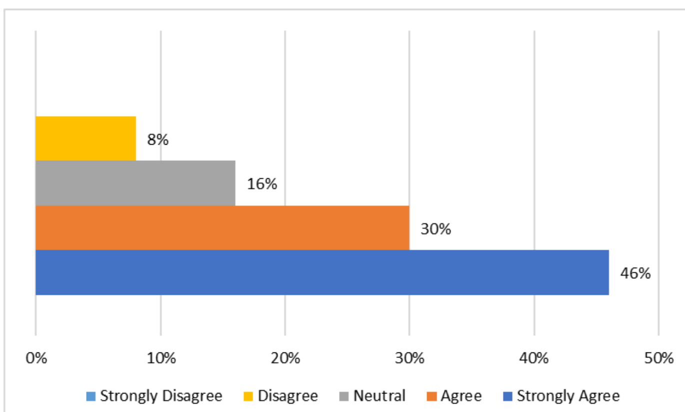


Figure 14: AI is smarter decision maker than humans

46% of the responders strongly agreed that AI makes smarter decisions than Humans, whereas 30% agreed that AI could make smarter decisions than Humans. 8% disagreed that AI can make smarter decisions than Humans. The remaining 16% were unsure if AI can make smarter decisions than humans or not. (Figure 14)

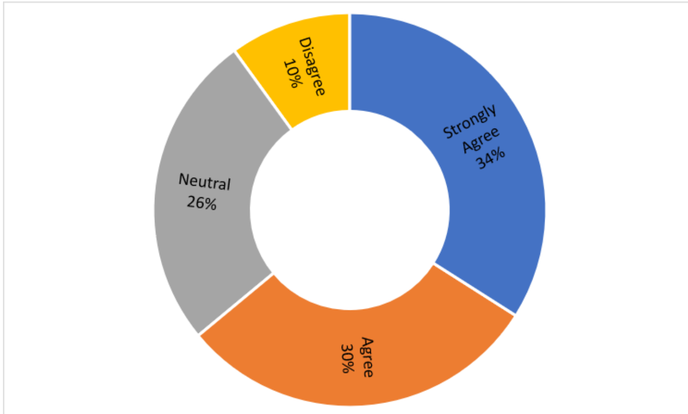


Figure 15: Need for Human decision-making

Of 50 responders, 64% (34 % strongly & 30% Agree) agreed that AI could eliminate the need for human decision-making. 10% disagreed with the statement, whereas 26% neither agreed nor disagreed with the statement. (Figure 15)

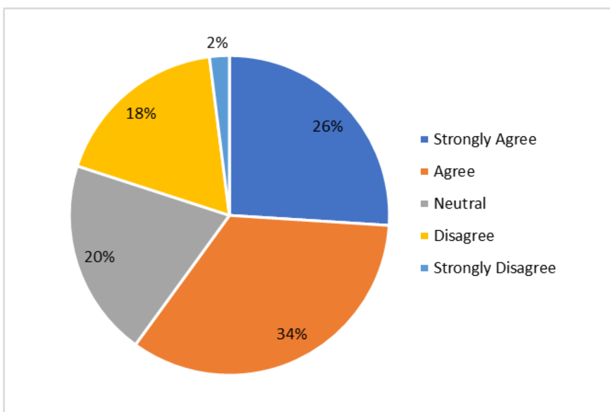


Figure 16: Challenges in maintaining strategic organisational decision making

When asked, “Using AI may create challenges in maintaining strategic decision making”, 60% agreed with the statement. On the other hand, 20% disagreed, and 20% neither agreed nor disagreed with the statement. (Figure 16)

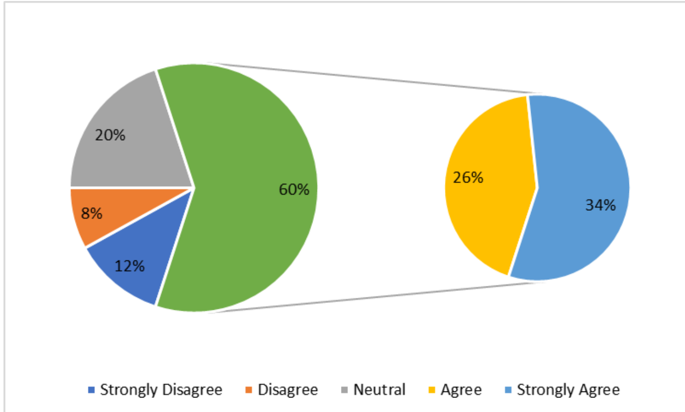


Figure 17: Dynamic decision-making theory

A combination of 60% (strongly agree & agree) agreed that "Dynamic decision-making theory can work as a guide to design the patterns of AI decision support”. 20% disagree with this statement, and 20% were unsure if "Dynamic decision-making theory can work as a guide to design the patterns of AI decision support”. (Figure 17)

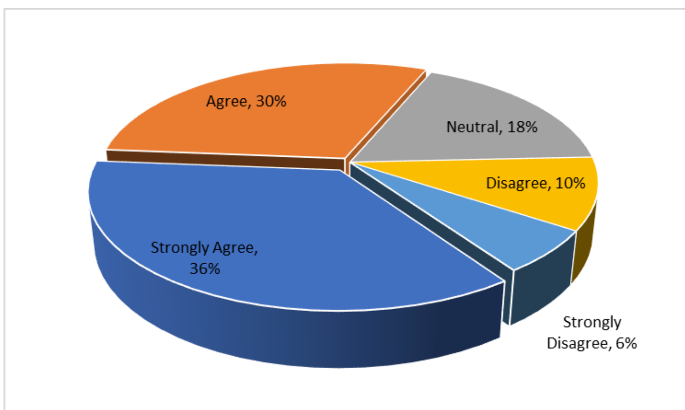


Figure 18: Use of AI in growth and success

Responders' opinions regarding the statement, "The use of AI helps businesses to grow and ensure success”, indicate that 36% strongly agree with the statement, with a further 30% also agreeing with the statement. 16% do not believe that " AI helps businesses to grow and ensure success”. The remaining 18% were unsure and remained neutral. (Figure 18)

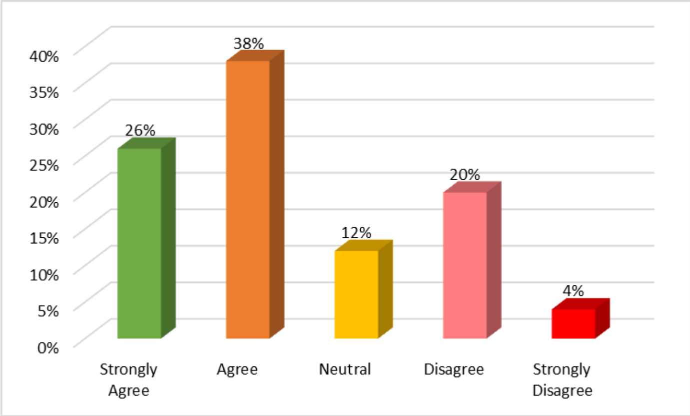


Figure 19: Impact of AI on the performance of employees and staff members

When asked for an opinion on the statement, "There is a significant impact of AI on the performance of employees and staff members working for organisational success and growth", 64% of the responders agreed with the statement, whereas 24% disagreed. 12% neither agreed nor disagreed with the statement. (Figure 19)

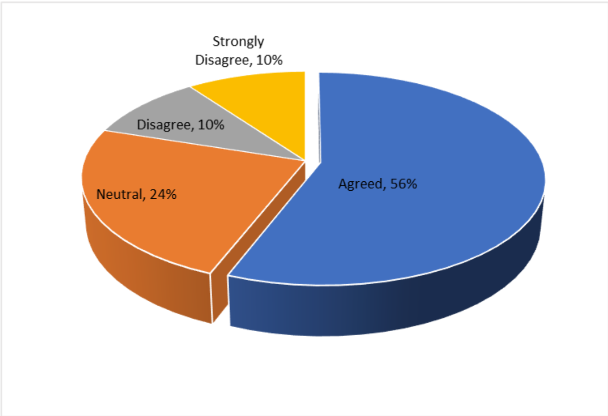


Figure 20: Challenges for AI developers and IT employees with the implication of AI

Of the 50 responders, 56% agreed (34% strongly agreed and 22% agreed) with the statement, "Is it challenging for IT employees and AI Developers to speed up the decision-making process with the implication of AI within the workplace". 20% disagreed with the statement, and 24% could not make their decision and remained neutral. (Figure 20)

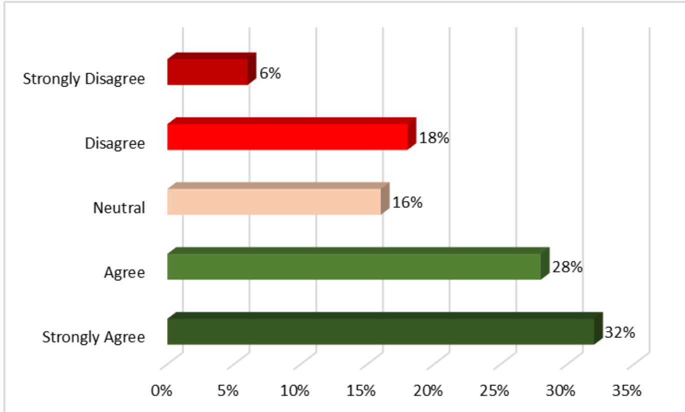


Figure 21: Interpretation of humans and technology in the decision-making process

32% of the responders strongly agree that "Incorporating Humans and Technology into decision making would significantly improve the growth and functioning of the businesses”. In addition, other 28% of the responders also agreed with the statement. However, 24% disagreed with the statement, and 16% remained neutral. (Figure 21)

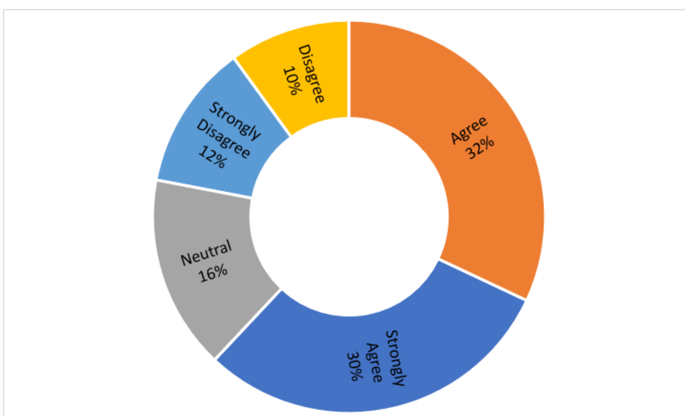


Figure 22: Successful implementation of AI for engagement of employees

Most responders agree that "Successful implementation of AI is achieved by focusing on the active engagement of employees and a step-by-step introduction of the process”, whilst 32% disagree with this statement. The remaining 16% of the people were unsure and remained neutral. (Figure 22)

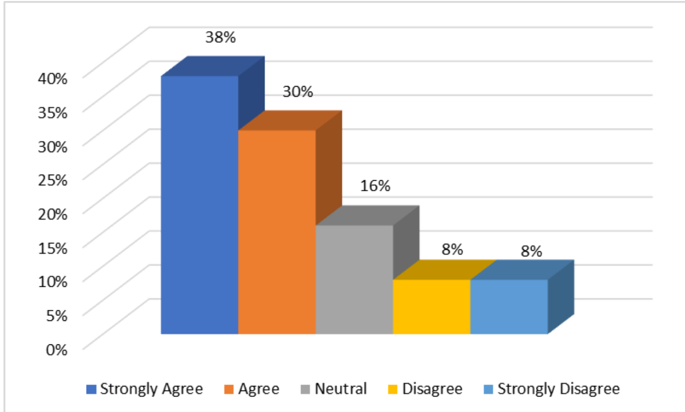


Figure 23: Soft skills play a vital role in incorporating AI into decision making

16% of the responders do not agree that "Soft skills like the ability to work in a team and think creatively play a crucial role in incorporating AI into the decision-making process". 68% agree that soft skills play a crucial role in incorporating AI into decision-making. The remaining 16% were unsure. (Figure 23)

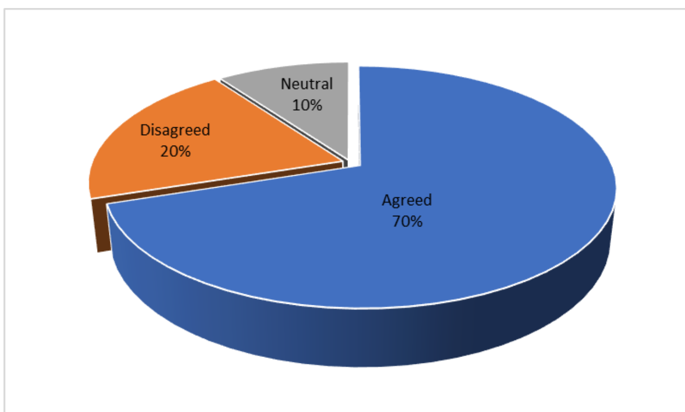


Figure 24: Determination of team performance issues

When asked for an opinion on performance issues, 70% agreed that "By keeping track of the difficulties faced by each IT Employee or staff worker, AI can determine which individuals in the team have performance issues". 20% disagreed with the statement, whereas 10% remained neutral. (Figure 24)

4.3. Descriptive Statistics

The SPSS software has been used for doing the descriptive statistics test from the sample of the top organisations using AI for decision-making, and whose case study instances will be represented in the research. The table below presents the statistics for using AI programmes to help speed up decision-making in the organisation.

Frequencies

		Gender	Awareness regarding the use of Artificial Intelligence in the Decision-Making Process	Artificial Intelligence (AI) plays an essential role in speeding up the Decision-Making Process	AI can make smarter decisions than humans or not	AI can eliminate the need for human decision-making or not	Using AI may create challenges in maintaining strategic organisational decision making	Dynamic decision-making theory can work as a guide to design patterns of AI decision support	The use of AI helps businesses to grow and ensure success	There is a significant impact of AI on the performance of employees and staff members working for organisational success and growth	Is it challenging for IT employees and AI Developers to speed up the decision-making process with the implication of AI within the workplace	Incorporating Humans and Technology into Decision-Making would significantly improve the growth and functioning of the businesses	Successful implementation of AI is achieved by focusing on the active engagement of the employees and a step-by-step introduction of the process	Soft skills like the ability to work in a team and think creatively play a crucial role in incorporating AI into the decision-making process	By keeping track of the difficulties faced by each IT Employee or staff worker, AI can determine which individuals in the team have performance issues
N	Valid	50	50	50	50	50	50	50	50	50	50	50	50	50	50
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		1.46	1.20	2.14	1.86	2.12	2.36	2.38	2.20	2.38	2.40	2.38	2.42	2.18	2.22
Median		1.00	1.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Std. Deviation		.542	.404	1.125	.969	1.003	1.120	1.354	1.212	1.193	1.325	1.276	1.341	1.257	1.130
Range		2	1	4	3	3	4	4	4	4	4	4	4	4	4
Minimum		1	1	1	1	1	1	1	1	1	1	1	1	1	1
Maximum		3	2	5	4	4	5	5	5	5	5	5	5	5	5
Percentiles	25	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	1.00	1.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	75	2.00	1.00	3.00	2.25	3.00	3.00	3.00	3.00	3.25	3.00	3.25	3.00	3.00	3.00

In the above analysis of the descriptive statistics test, it has been found that the mean of top organisations using AI for decision-making was around 1.2 to 2.42 (Figure 25). Moreover, on the other hand, it has been found that the standard deviation means of top organisations that have been using AI for the decision-making process was 0.4 to 1.34. From this, it can be said that the mean is higher than the standard deviation value. The statements used in the close-ended questionnaire were asked from the respondents, and their responses, the descriptive statistics test was performed. The analysis shows that in the sample of top organisations using AI for decision-making, the minimum observed mean 1, and the maximum is 5.

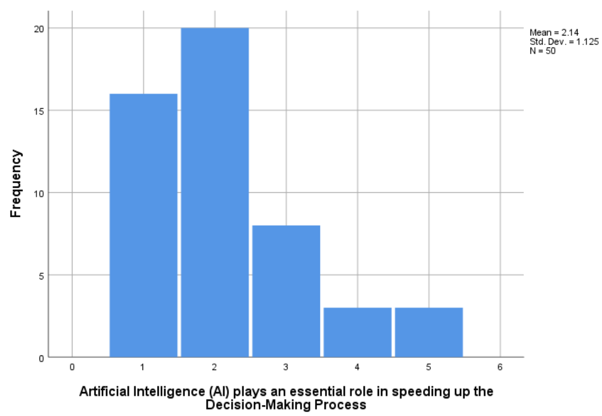


Figure 25: The role played by AI in speeding the decision-making process

Considering the sample of top organisations using AI for the decision-making process, it has been found that the distribution of AI, which plays an essential role in speeding up the decision-making procedure, was bimodal. In several cases, the organisations fall between 10% and 55%.

Correlations

		Gender	Awareness regarding the use of Artificial Intelligence in the Decision-Making Process	Artificial Intelligence (AI) plays an essential role in speeding up the Decision-Making Process	AI can make smarter decisions than humans or not	AI can eliminate the need for human decision-making or not	Using AI may create challenges in maintaining strategic organisational decision making	Dynamic decision-making theory can work as a guide to design patterns of AI decision support	The use of AI helps businesses to grow and ensure success	There is a significant impact of AI on the performance of employees and staff members working for organisational success and growth	Is it challenging for IT employees and AI Developers to speed up the decision-making process with the implication of AI within the workplace	Incorporating Humans and Technology into Decision-Making would significantly improve the growth and functioning of the businesses	Successful implementation of AI is achieved by focusing on the active engagement of the employees and a step-by-step introduction of the process	Soft skills like the ability to work in a team and think creatively play a crucial role in incorporating AI into the decision-making process	By keeping track of the difficulties faced by each IT Employee or staff worker, AI can determine which individuals in the team have performance issues
Gender	Pearson Correlation	1	-0.056	.327*	.397**	0.122	-0.043	0.063	.447**	0.197	.307*	.332*	0.178	0.056	0.065
	Sig. (2-tailed)		0.7	0.02	0.004	0.4	0.767	0.665	0.001	0.17	0.03	0.019	0.217	0.701	0.656
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Awareness regarding the use of Artificial Intelligence in the Decision-Making Process	Pearson Correlation	-0.056	1	-0.153	0.125	0.191	0.198	0.007	-0.167	-0.119	0.114	0.166	0.143	0.048	-0.054
	Sig. (2-tailed)	0.7		0.29	0.387	0.183	0.167	0.959	0.247	0.412	0.429	0.249	0.322	0.739	0.711
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Artificial Intelligence (AI) plays an essential role in speeding up the Decision-Making Process	Pearson Correlation	.327*	-0.153	1	.355*	0.22	0.121	-0.049	.533**	.370**	0.167	0.062	0.123	0.126	.393**
	Sig. (2-tailed)	0.02	0.29		0.011	0.125	0.402	0.735	0	0.008	0.246	0.67	0.397	0.383	0.005
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
AI can make smarter decisions than humans or not	Pearson Correlation	.397**	0.125	.355*	1	0.228	0.16	0.041	.337*	.347*	.347*	0.143	-0.032	.289*	0.196
	Sig. (2-tailed)	0.004	0.387	0.011		0.112	0.267	0.775	0.017	0.014	0.014	0.322	0.824	0.042	0.172
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
AI can eliminate the need for human decision-making or not	Pearson Correlation	0.122	0.191	0.22	0.228	1	.360*	0.266	0.248	0.08	.485**	.330*	0.053	0.128	0.228
	Sig. (2-tailed)	0.4	0.183	0.125	0.112		0.01	0.061	0.082	0.578	0	0.019	0.716	0.375	0.111
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Using AI may create challenges in maintaining strategic organisational decision making	Pearson Correlation	-0.043	0.198	0.121	0.16	.360*	1	.433**	0.066	0.17	.300*	.559**	0.142	-0.003	.291*
	Sig. (2-tailed)	0.767	0.167	0.402	0.267	0.01		0.002	0.648	0.237	0.034	0	0.326	0.981	0.041
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Dynamic decision-making theory can work as a guide to design patterns of AI decision support	Pearson Correlation	0.063	0.007	-0.049	0.041	0.266	.433**	1	-0.047	-0.154	0.13	.316*	.371**	-0.113	-0.042
	Sig. (2-tailed)	0.665	0.959	0.735	0.775	0.061	0.002		0.744	0.284	0.369	0.025	0.008	0.435	0.77
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
The use of AI helps businesses to grow and ensure success	Pearson Correlation	.447**	-0.167	.533**	.337*	0.248	0.066	-0.047	1	.313*	-0.051	0.069	0.01	0.204	.474**
	Sig. (2-tailed)	0.001	0.247	0	0.017	0.082	0.648	0.744		0.027	0.726	0.636	0.945	0.156	0.001
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
There is a significant impact of AI on the performance of employees and staff members working for organisational success and growth	Pearson Correlation	0.197	-0.119	.370**	.347*	0.08	0.17	-0.154	.313*	1	0.199	0.131	0.153	0.158	.315*
	Sig. (2-tailed)	0.17	0.412	0.008	0.014	0.578	0.237	0.284	0.027		0.166	0.364	0.288	0.274	0.026
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Is it challenging for IT employees and AI Developers to speed up the decision-making process with the implication of AI within the workplace	Pearson Correlation	.307*	0.114	0.167	.347*	.485**	.300*	0.13	-0.051	0.199	1	0.258	-0.039	0.189	0.022
	Sig. (2-tailed)	0.03	0.429	0.246	0.014	0	0.034	0.369	0.726	0.166		0.07	0.788	0.189	0.88
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Incorporating Humans and Technology into Decision-Making would significantly improve the growth and functioning of the businesses	Pearson Correlation	.332*	0.166	0.062	0.143	.330*	.559**	.316*	0.069	0.131	0.258	1	0.263	-0.158	0.111
	Sig. (2-tailed)	0.019	0.249	0.67	0.322	0.019	0	0.025	0.636	0.364	0.07		0.065	0.273	0.444
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Successful implementation of AI is achieved by focusing on the active engagement of the employees and a step-by-step introduction of the process	Pearson Correlation	0.178	0.143	0.123	-0.032	0.053	0.142	.371**	0.01	0.153	-0.039	0.263	1	0.184	0.059
	Sig. (2-tailed)	0.217	0.322	0.397	0.824	0.716	0.326	0.008	0.945	0.288	0.788	0.065		0.2	0.684
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Soft skills like the ability to work in a team and think creatively play a crucial role in incorporating AI into the decision-making process	Pearson Correlation	0.056	0.048	0.126	.289*	0.128	-0.003	-0.113	0.204	0.158	0.189	-0.158	0.184	1	.446**
	Sig. (2-tailed)	0.701	0.739	0.383	0.042	0.375	0.981	0.435	0.156	0.274	0.189	0.273	0.2		0.001
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
By keeping track of the difficulties faced by each IT Employee or staff worker, AI can determine which individuals in the team have performance issues	Pearson Correlation	0.065	-0.054	.393**	0.196	0.228	.291*	-0.042	.474**	.315*	0.022	0.111	0.059	.446**	1
	Sig. (2-tailed)	0.656	0.711	0.005	0.172	0.111	0.041	0.77	0.001	0.026	0.88	0.444	0.684	0.001	
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

According to the above correlation data, it has been found that AI has a huge significant association with top organisations' decision-making processes because it helps enhance their performance and productivity level. Further, it has been observed that AI has a favourable and noteworthy relationship with the decision-making process of top organisations, as the coefficient values lie between 0.5 and 1.

In addition, the significant value must be less than 0.005 because it shows effective, favourable, and significant connections between the variables. After doing a correlation test, the analysis shows that top organisations using AI for the decision-making process significantly impact the organisation's performance – as the significance level is lower than 0.005.

Chapter 5: Conclusion and Recommendations

5.1. Conclusion

Therefore, from the above discussion, it has been concluded that every advertising choice involves several factors and complications. To successfully market and sell a product, one must first have an intimate familiarity with the wants and needs of the target market. Equally important for both short- and long-term success in marketing is understanding how consumers' preferences are likely to evolve.

Artificial intelligence (AI) modelling and simulation approaches provide trustworthy insight into customer personas. Consumer behaviour forecasting is the possible use of these methods. The AI system may provide decision support by collecting data, making predictions, and analysing trends in real-time with the help of a Decision Support System. The assembly line is obsolete because of artificial intelligence's automated efficiency offered to modern business operations. AI has been able to speed up procedures and give decision-makers trustworthy knowledge in several corporate operations, including marketing and distribution. Automating processes like market segmentation and campaign management has helped marketers make better decisions and move faster. By learning more about their clientele, businesses may improve the quality of their interactions with those clients. Among the most critical functions of any robust CRM platform is marketing automation.

A significant benefit for many stores has been the automation of distribution processes made possible by AI. Retailers may better anticipate and respond to customer product requests with the help of AI-enhanced monitoring and control. Amazon is a prime illustration of the rise of e-commerce. It bought the robotics company Kiva Systems, which made machines for use in warehouses, in 2012. Since its introduction, Kiva robots have been responsible for stock checking, restocking, and order processing. For that matter, they can even assist with heavy lifting. Amazon has made great strides in efficiency since the days when human labour was required to complete menial tasks. Since neither a Terminator nor a Replicant is lurking nearby, AI's only real threat is its potential. One may argue that the more realistic fear of automation displacing human workers is unnecessary. According to experts, AI can improve people's work lives and make them more productive.

Furthermore, there is little doubt that this is true when considering selecting choices. Better choices may be made for the organisation and its workers when decision-makers and executives have access to trustworthy data analysis, suggestions, and follow-ups via AI technologies. They contribute to the team's success in more ways than one, and AI also boosts the company's ability to compete successfully.

The gap exists in the absence of AI systems equipped to manage the vast quantities of data at hand. Although, about 80% of all data, such as text messages, photos, and audio files, is unstructured. There is currently no human or artificial intelligence capable of sorting through this volume of data to extract valuable insights. As a result, firms may improve their decision-making in critical business processes by using AI-based business intelligence solutions. By doing so, businesses may not only reap the full advantages of a data-driven culture but also consider the broadest range of available data when making strategic moves.

5.2. Recommendations

Considering the above discussion, it has been found that some areas require some recommendations and strategies to ensure the success and functioning of the overall management industry with the practical implication of AI that directly incorporates the smooth functioning of the decision-making power of the managers and businesses. So, some of the recommendations for this study are described below in a detailed manner:

- Executives often need to consider several variables while making complicated decisions. When there is an excessive amount of information to process, the decision-maker runs the risk of becoming paralysed. However, in contrast to human limitations, a computer can process numerous inputs without becoming overwhelmed or confused. A machine can make the best rational choice given instructions that teach it to utilise probability (Maclaurin et al., 2019).

- Humans will continue to make decisions until we can give AI emotional intelligence. An automated system may be trusted to make choices on less complex activities that do not call for the human qualities of empathy and experience that underpin good commercial judgement. As has been emphasised by academics and authors, the capacity to make trade-offs when necessary is another crucial feature of sound judgement that cannot be entrusted to AI. This is because providing reliable advice depends on in-depth familiarity with the organisation's culture, history, and current state to identify potential threats and opportunities. However, AI can and should continue to be included in the judging process. Its job is to lay forth all the options for the human to make an informed decision.
- Many firms are already using predictive analytics via data mining to improve decision-making. By studying a dataset and making educated predictions about what will happen at a later date, organisations may use predictive analytics to plan. Additionally, machine learning, which is also employed in predictive analytics, is brought to the table by AI. Machine learning differs from data mining in that the latter seeks to uncover patterns in huge data sets, while the former is created to learn from and independently respond to such data (Choudhury, 2020).

Hence, numerous psychological research has shown that decision quality steadily declines when people are under pressure to make numerous choices in a short time. Because customers are often mentally and physically drained from making several choices throughout the store, retailers strategically place sugary snacks and candies at checkout counters. However, algorithms do not have nearly as many flaws, and they assist CEOs in avoiding making poor choices due to fatigue since they can make intelligent choices at any moment.

5.3. Limitations of the Study

The research procedure will take longer and need more effort because this study employs primary and secondary strategies to obtain information, such as legal sources. Since this is the case, research loses some of its significance. Data mining for one purpose may be inaccurate, irrelevant, or out of date, making it impossible to glean meaningful insights from them. The researcher can make up for these flaws by presenting the study's findings comprehensively, scientifically, and psychologically. On the other hand, it is also possible for the researcher to give data that is neither useful nor relevant to the topic. This study may be hampered by the fact that its intended participant may be unwilling to disclose information due to the topic's sensitive nature.

5.4. Managerial Contribution

Management's combined efforts have been crucial to the development and success of the research project. Managers can have a significant impact on the company's culture and the decisions made at all levels of the organisation if they demonstrate a willingness to adopt the implication of Artificial Intelligence within the workplace to take better decisions related to the activities required to maintain an influential advertising management culture and the success of businesses (Gavaghan, 2019).

Bibliography

Agrawal, A., Gans, J. and Goldfarb, A. (2018). *A Simple Tool to Start Making Decisions with the Help of AI*. [online] Harvard Business Review. Available at: https://hbr.org/2018/04/a-simple-tool-to-start-making-decisions-with-the-help-of-ai.

Akerkar, R., 2019. *Artificial intelligence for business*. Springer.

Akhtar, D.M.I., 2016. Research design. *Research Design (February 1, 2016)*.

Alase, A., 2017. The interpretative phenomenological analysis (IPA): A guide to a good qualitative research approach. *International Journal of Education and Literacy Studies*, *5*(2), pp.9-19.

Alsheibani, S.A., Cheung, D. and Messom, D., 2019. Factors inhibiting the adoption of artificial intelligence at organizational-level: A preliminary investigation.

Alyoubi, B.A., 2015. Decision support system and knowledge-based strategic management. *Procedia Computer Science*, *65*, pp.278-284.

Armat, M.R., Assarroudi, A., Rad, M., Sharifi, H. and Heydari, A., 2018. Inductive and deductive: Ambiguous labels in qualitative content analysis. *The Qualitative Report*, *23*(1), pp.219-221.

Asan, O., Bayrak, A.E. and Choudhury, A., 2020. Artificial intelligence and human trust in healthcare: focus on clinicians. *Journal of medical Internet research*, *22*(6), p.e15154.

Azungah, T., 2018. Qualitative research: deductive and inductive approaches to data analysis. *Qualitative Research Journal*.

Bader, V. and Kaiser, S., 2019. Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organisation*, *26*(5), pp.655-672.

Barber, O., 2021. *Artificial Intelligence in Decision Making - Big Overview from InData Labs*. [online] InData Labs. Available at: <https://indatalabs.com/blog/artificial-intelligence-decision-making> [Accessed 22 June 2022].

Barocas, S. and Selbst, A.D., 2016. Big data's disparate impact. *Calif. L. Rev.*, *104*, p.671.

Berryhill, J., Heang, K.K., Clogher, R. and McBride, K., 2019. Hello, World: Artificial intelligence and its use in the public sector.

Bienhaus, F. and Haddud, A., 2018. Procurement 4.0: factors influencing the digitisation of procurement and supply chains. *Business Process Management Journal*.

Blasch, E., Cruise, R., Aved, A., Majumder, U. and Rovito, T., 2019. Methods of AI for multimodal sensing and action for complex situations. *AI Magazine*, *40*(4), pp.50-65.

Bogosian, K., 2017. Implementation of moral uncertainty in intelligent machines. *Minds and Machines*, *27*(4), pp.591-608.

Bolander, T., 2019. What do we lose when machines take the decisions?. *Journal of Management and Governance*, *23*(4), pp.849-867.

Bolton, C., Machová, V., Kovacova, M. and Valaskova, K., 2018. The power of human–machine collaboration: Artificial intelligence, business automation, and the smart economy. *Economics, Management, and Financial Markets*, *13*(4), pp.51-56.

Boone, T., Ganeshan, R., Jain, A. and Sanders, N.R., 2019. Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting*, *35*(1), pp.170-180.

Brannen, J. ed., 2017. *Mixing methods: Qualitative and quantitative research*. Routledge.

Canhoto, A.I. and Clear, F., 2020. Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, *63*(2), pp.183-193.

Carbone, E., Georgalos, K. and Infante, G., 2019. Individual vs. group decision-making: an experiment on dynamic choice under risk and ambiguity. *Theory and decision*, *87*(1), pp.87-122.

Cervantes, J.A., Rodríguez, L.F., López, S., Ramos, F. and Robles, F., 2016. Autonomous agents and ethical decision-making. *Cognitive Computation*, *8*(2), pp.278-296.

Charness, G. and Sutter, M., 2012. Groups make better self-interested decisions. *Journal of Economic Perspectives*, *26*(3), pp.157-76.

Cheng, M. and Foley, C., 2018. The sharing economy and digital discrimination: The case of Airbnb. *International Journal of Hospitality Management*, *70*, pp.95-98.

Chernov, A. and Chernova, V., 2019. Artificial Intelligence In Management: Challenges And Opportunities. *Economic and Social Development: Book of Proceedings*, pp.133-140.

Duan, Y., Edwards, J.S. and 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, pp.63-71.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A. and Galanos, V., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, p.101994.

Eukhost, 2018. *7 Benefits of Artificial Intelligence for Business*. [online] Available at: <https://www.eukhost.com/blog/webhosting/7-benefits-of-artificial-intelligence-for-business/> [Accessed 22 June 2022].

Feng, Y., Duives, D., Daamen, W. and Hoogendoorn, S., 2021. Data collection methods for studying pedestrian behaviour: A systematic review. *Building and Environment*, *187*, p.107329.

Fiori, S., 2011. Forms of bounded rationality: The reception and redefinition of Herbert A. Simon's perspective. *Review of Political Economy*, *23*(4), pp.587-612.

Forbes, 2018. *10 ways Artificial Intelligence will change recruitment practices*. [online] Available at: <https://www.forbes.com/sites/forbescoach escouncil/2018/08/10/10-ways-artificial-intelligence-willchange-recruitment-practices/#33e620293a2> [Accessed 22 June 2022].

Fountaine, T., McCarthy, B. and Saleh, T., 2019. Building the AI-powered organization. *Harvard Business Review*, *97*(4), pp.62-73.

Fredrickson, J.W., 1984. The comprehensiveness of strategic decision processes: Extension, observations, future directions. *Academy of Management journal*, *27*(3), pp.445-466.

Fu, X., Dong, M. and Han, G., 2017. Coordinating a trust-embedded two-tier supply chain by options with multiple transaction periods. *International Journal of Production Research*, *55*(7), pp.2068-2082.

Gajjar, D., 2013. Ethical consideration in research. *Education*, *2*(7), pp.8-15.

Gartner, 2019. *Gartner Identifies Top 10 Data and Analytics Technology Trends for 2019*. [online] Gartner. Available at: <https://www.gartner.com/en/newsroom/press-releases/2019-02-18-gartner-identifies-top-10-data-and-analytics-technolo> [Accessed 17 May 2022].

Ghosh, A., Chakraborty, D. and Law, A., 2018. Artificial intelligence in Internet of things. *CAAI Transactions on Intelligence Technology*, *3*(4), pp.208-218.

Giubilini, A. and Savulescu, J., 2018. The artificial moral advisor. The "ideal observer" meets artificial intelligence. *Philosophy & technology*, *31*(2), pp.169-188.

Gonzalez, C., Lerch, J.F. and Lebiere, C., 2003. Instance-based learning in dynamic decision making. *Cognitive Science*, *27*(4), pp.591-635.

Goralski, M.A. and Tan, T.K., 2020. Artificial intelligence and sustainable development. *The International Journal of Management Education*, *18*(1), p.100330.

Guha Thakurta, S. and Chetty, P., 2015. Understanding research philosophy. *Knowledge Tank*.

Haleem, A., Javaid, M. and Khan, I.H., 2019. Current status and applications of Artificial Intelligence (AI) in the medical field: An overview. Current Medicine Research and Practice, 9(6), pp.231-237.

Haruvy, E., Katok, E., Ma, Z. and Sethi, S., 2019. Relationship-specific investment and hold-up problems in supply chains: Theory and experiments. *Business Research*, *12*(1), pp.45-74.

Hertz, N. and Wiese, E., 2019. Good advice is beyond all price, but what if it comes from a machine?. *Journal of Experimental Psychology: Applied*, *25*(3), p.386.

Huang, M.H. and Rust, R.T., 2018. Artificial intelligence in service. *Journal of Service Research*, *21*(2), pp.155-172.

Huang, M.H., Rust, R. and Maksimovic, V., 2019. The feeling economy: Managing in the next generation of artificial intelligence (AI). *California Management Review*, *61*(4), pp.43-65.

InData Labs, 2021. *Big Data: Revolution To Transform Business Models*. [online] InData Labs. Available at: <https://indatalabs.com/blog/impact-of-big-data-on-business> [Accessed 22 June 2022].

Jarrahi, M.H., 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organisational decision making. *Business horizons*, *61*(4), pp.577-586.

Julmi, C., 2019. When rational decision-making becomes irrational: a critical assessment and re-conceptualization of intuition effectiveness. *Business Research*, *12*(1), pp.291-314.

Kahneman, D., 2003. Maps of bounded rationality: Psychology for behavioral economics. *American economic review*, *93*(5), pp.1449-1475.

Kephart, J.O. and Walsh, W.E., 2004, June. An artificial intelligence perspective on autonomic computing policies. In *Proceedings. Fifth IEEE International Workshop on Policies for Distributed Systems and Networks, 2004. POLICY 2004.* (pp. 3-12). IEEE.

Kim, H., Sefcik, J.S. and Bradway, C., 2017. Characteristics of qualitative descriptive studies: A systematic review. *Research in nursing & health*, *40*(1), pp.23-42.

Kirchkamp, O. and Strobel, C., 2019. Sharing responsibility with a machine. *Journal of Behavioral and Experimental Economics*, *80*, pp.25-33.

Klumpp, M. and Zijm, H., 2019. Logistics innovation and social sustainability: How to prevent an artificial divide in human–computer interaction. *Journal of Business Logistics*, *40*(3), pp.265-278.

Kolbjørnsrud, V., Amico, R. and Thomas, R.J., 2017. Partnering with AI: how organisations can win over skeptical managers. *Strategy & Leadership*.

Kourouxous, T. and Bauer, T., 2019. Violations of dominance in decision-making. *Business Research*, *12*(1), pp.209-239.

Kugler, T., Kausel, E.E. and Kocher, M.G., 2012. Are groups more rational than individuals? A review of interactive decision making in groups. *Wiley Interdisciplinary Reviews: Cognitive Science*, *3*(4), pp.471-482.

Kumar, R., 2018. *Research methodology: A step-by-step guide for beginners*. Sage.

Kuzior, A., Kwilinski, A. and Tkachenko, V., 2019. Sustainable development of organisations based on the combinatorial model of artificial intelligence. *Entrepreneurship and Sustainability Issues*, *7*(2), p.1353.

L'heureux, A., Grolinger, K., Elyamany, H.F. and Capretz, M.A., 2017. Machine learning with big data: Challenges and approaches. *Ieee Access*, *5*, pp.7776-7797.

Lawrence, T., 1991. Impacts of artificial intelligence on organisational decision making. *Journal of Behavioral Decision Making*, *4*(3), pp.195-214.

Legg, S. and Hutter, M., 2007. Universal intelligence: A definition of machine intelligence. *Minds and machines*, *17*(4), pp.391-444.

Leonardi, P.M., 2020. COVID-19 and the new technologies of organizing: digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. *Journal of Management Studies*.

Lepri, B., Oliver, N., Letouzé, E., Pentland, A. and Vinck, P., 2018. Fair, transparent, and accountable algorithmic decision-making processes. *Philosophy & Technology*, *31*(4), pp.611-627.

Leyer, M. and Schneider, S., 2021. Decision augmentation and automation with artificial intelligence: Threat or opportunity for managers?. *Business Horizons*, *64*(5), pp.711-724.

Leyer, M., 2020. *Decision-making with artificial intelligence: Towards a novel conceptualization of patterns*. [online] Fim-rc.de. Available at: <https://www.fim-rc.de/Paperbibliothek/Veroeffentlicht/1125/wi-1125.pdf> [Accessed 22 June 2022].

Leyer, M., Oberlaender, A., Dootson, P. and Kowalkiewicz, M., 2020, June. Decision-making with artificial intelligence: Towards a novel conceptualization of patterns. In *PACIS* (p. 224).

Lin-Greenberg, E., 2020. Allies and artificial intelligence: Obstacles to operations and decision-making (Spring 2020). *Texas National Security Review*.

Lismont, J., Vanthienen, J., Baesens, B. and Lemahieu, W., 2017. Defining analytics maturity indicators: A survey approach. *International Journal of Information Management*, *37*(3), pp.114-124.

Liu, S., Leat, M., Moizer, J., Megicks, P. and Kasturiratne, D., 2013. A decision-focused knowledge management framework to support collaborative decision making for the lean supply chain management. *International Journal of Production Research*, *51*(7), pp.2123-2137.

Loh, E., 2018. Medicine and the rise of the robots: a qualitative review of recent advances of artificial intelligence in health. *BMJ leader*, pp.leader-2018.

Long, Q., 2018. Data-driven decision-making for supply chain networks with agent-based computational experiment. *Knowledge-Based Systems*, *141*, pp.55-66.

Lyons, J.B., Clark, M.A., Wagner, A.R. and Schuelke, M.J., 2017. Certifiable trust in autonomous systems: Making the intractable tangible. *AI Magazine*, *38*(3), pp.37-49.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S. and Söllner, M., 2019. AI-based digital assistants. *Business & Information Systems Engineering*, *61*(4), pp.535-544.

Makridakis, S., 2017. The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, pp.46-60.

Martin, K., Shilton, K. and Smith, J., 2019. Business and the ethical implications of technology: Introduction to the symposium. *Journal of Business Ethics*, *160*(2), pp.307-317.

McCarthy, J., Minsky, M.L., Rochester, N. and Shannon, C.E., 2006. A proposal for the Dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine*, *27*(4), pp.12-12.

Mckinsey, 2018. *NOTES FROM THE AI FRONTIER MODELING THE IMPACT OF AI ON THE WORLD ECONOMY*. [online] Available at: <https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.ashx> [Accessed 22 June 2022].

Mckinsey, 2021. *The state of AI in 2020*. [online] Available at: <https://www.mckinsey.com/business-functions/quantumblack/our-insights/global-survey-the-state-of-ai-in-2020> [Accessed 17 May 2022].

Melnyk, S.A., Narasimhan, R. and DeCampos, H.A., 2014. Supply chain design: issues, challenges, frameworks and solutions. *International Journal of Production Research*, *52*(7), pp.1887-1896.

Mesir, M., 2019. The Role of Artificial Intelligence in Decision Making in Small Businesses. *Indian Journal of Science and Technology*, 12(18), pp.1-6.

Metzger, O. and Spengler, T., 2019. Modelling rational decisions in ambiguous situations: a multi-valued logic approach. *Business Research*, *12*(1), pp.271-290.

Migliore, L.A. and Chinta, R., 2017. Demystifying the Big Data Phenomenon for Strategic Leadership. *SAM Advanced Management Journal (07497075)*, *82*(1).

Moreira, M. and Tjahjono, B., 2016. Applying performance measures to support decision-making in supply chain operations: a case of beverage industry. *International Journal of Production Research*, *54*(8), pp.2345-2365.

Nguyen, T., Li, Z.H.O.U., Spiegler, V., Ieromonachou, P. and Lin, Y., 2018. Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, *98*, pp.254-264.

Nilsson, N.J., 2009. *The quest for artificial intelligence*. Cambridge University Press.

O'Gorman, K., Lochrie, S. and Watson, A., 2014. Research philosophy and case studies. *Research Methods for Business & Management*, pp.152-172.

Ott, R.L. and Longnecker, M.T., 2015. *An introduction to statistical methods and data analysis*. Cengage Learning.

Park, Y., El Sawy, O.A. and Fiss, P., 2017. The role of business intelligence and communication technologies in organisational agility: a configurational approach. *Journal of the association for information systems*, *18*(9), p.1.

Parry, K., Cohen, M. and Bhattacharya, S., 2016. Rise of the machines: A critical consideration of automated leadership decision making in organisations. *Group & Organisation Management*, *41*(5), pp.571-594.

Paschen, U., Pitt, C. and Kietzmann, J., 2020. Artificial intelligence: Building blocks and an innovation typology. *Business Horizons*, *63*(2), pp.147-155.

Pereira, J. and Vilà, M., 2016. A new model for supply chain network design with integrated assembly line balancing decisions. *International Journal of Production Research*, *54*(9), pp.2653-2669.

Rathi, D.R., 2018. Artificial intelligence and the future of hr practices. International Journal of Applied Research, 4(6), pp.113-116.

Resnik, M.D., 1987. *Choices: An introduction to decision theory*. U of Minnesota Press.

Riedl, M.O., 2019. Human-centered artificial intelligence and machine learning. *Human Behavior and Emerging Technologies*, *1*(1), pp.33-36.

Roth, S., Robbert, T. and Straus, L., 2015. On the sunk-cost effect in economic decision-making: a meta-analytic review. *Business research*, *8*(1), pp.99-138.

Rousseau, D.M., 2018. Making evidence-based organisational decisions in an uncertain world. *Organisational Dynamics*, *47*(3), pp.135-146.

Schneider, S. and Leyer, M., 2019. Me or information technology? Adoption of artificial intelligence in the delegation of personal strategic decisions. *Managerial and Decision Economics*, *40*(3), pp.223-231.

Schwenk, C. and Valacich, J.S., 1994. Effects of devil' s advocacy and dialectical inquiry on individuals versus groups. *Organisational behaviour and human decision processes*, *59*(2), pp.210-222.

Shank, D.B., DeSanti, A. and Maninger, T., 2019. When are artificial intelligence versus human agents faulted for wrongdoing? Moral attributions after individual and joint decisions. *Information, Communication & Society*, *22*(5), pp.648-663.

Shrestha, Y.R., Ben-Menahem, S.M. and Von Krogh, G., 2019. Organisational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), pp.66-83.

Silva, S. and Kenney, M., 2018. Algorithms, platforms, and ethnic bias: An integrative essay. *Phylon (1960-)*, *55*(1 & 2), pp.9-37.

Simon, H.A., 1995. Artificial intelligence: an empirical science. *Artificial Intelligence*, *77*(1), pp.95-127.

Starita, L., 2021. *Would You Let Artificial Intelligence Make Your Pay Decisions?*. [online] Gartner. Available at: <https://www.gartner.com/smarterwithgartner/would-you-let-artificial-intelligence-make-your-pay-decisions> [Accessed 22 June 2022].

Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J. and Machtynger, L., 2020. Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. *The Bottom Line*, *33*(2), pp.183-200.

Sullivan, D., 2015. *How Machine Learning Works, As Explained By Google*. [online] MarTech. Available at: <https://martech.org/how-machine-learning-works/> [Accessed 22 June 2022].

Surden, H., 2018. Artificial intelligence and law: An overview. *Ga. St. UL Rev.*, *35*, p.1305.

Tabesh, P., Mousavidin, E. and Hasani, S., 2019. Implementing big data strategies: A managerial perspective. *Business Horizons*, *62*(3), pp.347-358.

Taylor, J., 2021. *AI decision making: the future of business intelligence - Peak*. [online] Peak. Available at: <https://peak.ai/hub/blog/ai-decision-making-the-future-of-business-intelligence/> [Accessed 17 May 2022].

Terziyan, V., Gryshko, S. and Golovianko, M., 2018. Patented intelligence: Cloning human decision models for Industry 4.0. *Journal of manufacturing systems*, *48*, pp.204-217.

Townsend, D.M. and Hunt, R.A., 2019. Entrepreneurial action, creativity, & judgment in the age of artificial intelligence. *Journal of Business Venturing Insights*, *11*, p.e00126.

Udell, M., Stehel, V., Kliestik, T., Kliestikova, J. and Durana, P., 2019. Towards a smart automated society: Cognitive technologies, knowledge production, and economic growth. *Economics, Management and Financial Markets*, *14*(1), pp.44-49.

Vaccaro, M. and Waldo, J., 2019. The effects of mixing machine learning and human judgment. *Communications of the ACM*, *62*(11), pp.104-110.

Von Krogh, G., 2018. Artificial intelligence in organisations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*.

Walters, N., 2021. *How Artificial Intelligence Can Help Small Businesses*. [online] Articles.bplans.com. Available at: <https://articles.bplans.com/how-artificial-intelligence-can-help-small-businesses/> [Accessed 22 June 2022].

Watson, H.J., 2017. Preparing for the cognitive generation of decision support. *MIS Quarterly Executive*, *16*(3).

Webb, H., Patel, M., Rovatsos, M., Davoust, A., Ceppi, S., Koene, A., Dowthwaite, L., Portillo, V., Jirotka, M. and Cano, M., 2019. “It would be pretty immoral to choose a random algorithm”: opening up algorithmic interpretability and transparency. *Journal of Information, Communication and Ethics in Society*.

Whittle, T., Gregova, E., Podhorska, I. and Rowland, Z., 2019. Smart manufacturing technologies: Data-driven algorithms in production planning, sustainable value creation, and operational performance improvement. *Economics, Management and Financial Markets*, *14*(2), pp.52-57.

Wong, P.H., 2020. Democratizing algorithmic fairness. *Philosophy & Technology*, *33*(2), pp.225-244.

Wright, S., O'Brien, B.C., Nimmon, L., Law, M. and Mylopoulos, M., 2016. Research design considerations. *Journal of graduate medical education*, *8*(1), pp.97-98.

Wright, S.A. and Schultz, A.E., 2018. The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, *61*(6), pp.823-832.

Xie, Q., 2016. Research design and methods. In *English Language Training in the Workplace* (pp. 99-116). Springer, Cham.

Xu, W., 2019. Toward human-centered AI: a perspective from human-computer interaction. *interactions*, *26*(4), pp.42-46.

Yang, Q., Steinfeld, A. and Zimmerman, J., 2019, May. Unremarkable ai: Fitting intelligent decision support into critical, clinical decision-making processes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1-11).

Zalaghi, H. and Khazaei, M., 2016. The role of deductive and inductive reasoning in accounting research and standard setting. *Asian Journal of Finance & Accounting*, *8*(1), pp.23-37.

Zerilli, J., Knott, A., Maclaurin, J. and Gavaghan, C., 2019. Transparency in algorithmic and human decision-making: is there a double standard?. *Philosophy & Technology*, *32*(4), pp.661-683.

Appendices

Survey Questionnaire

Section-(1)

Socio-Demographics characteristics of the Respondents

Instruction: **Please tick any of the options you consider to be the most Appropriate**

1. **GENDER**. Male [ ] Female [ ] Prefer not to Say [ ]

2. **AGE**: 18-30 [ ] 30-45 [ ] 45-55 [ ] Above 55 [ ]

3. **PROFESSION**: IT Employees [ ] IT Experts [ ] AI Developers [ ] AI Designers [ ]

4. **Awareness regarding the use of Artificial Intelligence in the Decision-Making Process**: Yes [ ] No [ ]

Section-(2)

INSTRUCTION: Please tick from any of the options you consider most appropriate.

(SA) - STRONGLY AGREE, (A) -AGREE, (N) - NEUTRAL, (D)- DISAGREE, (SD) - STRONGLY DISAGREE.

S/N	QUESTION	1 (SA)	2 (A)	3 (N)	4 (D)	5 (SD)
1.	Artificial Intelligence (AI) plays an essential role in speeding up the Decision-Making Process					
2.	AI can make smarter decisions than humans or not					
3.	AI can eliminate the need for human decision-making or not					

S/N	QUESTION	1 (SA)	2 (A)	3 (N)	4 (D)	5 (SD)
4.	Using AI may create challenges in maintaining strategic organisational decision making					
5.	Dynamic decision-making theory can work as a guide to design patterns of AI decision support					
6.	The use of AI helps businesses to grow and ensure success					
7.	There is a significant impact of AI on the performance of employees and staff members working for organisational success and growth					
8.	Is it challenging for IT employees and AI Developers to speed up the decision-making process with the implication of AI within the workplace					
9.	Incorporating Humans and Technology into Decision-Making would significantly improve the growth and functioning of the businesses					
10.	Successful implementation of AI is achieved by focusing on the					

S/N	QUESTION	1 (SA)	2 (A)	3 (N)	4 (D)	5 (SD)
	active engagement of the employees and a step-by-step introduction of the process					
11.	Soft skills like the ability to work in a team and think creatively play a crucial role in incorporating AI into the decision-making process					
12.	By keeping track of the difficulties faced by each IT Employee or staff worker, AI can determine which individuals in the team have performance issues					