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Strategic Thinking - Thesis

Big Data and Machine Learning
Strategic Decisions In a VUCA World

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Abstract

The world we live in today has become more complex, turbulent and unpredictable than ever before. One of the main reasons for this is the emergence of the digital transformation and everything that comes with it, from technological advancements in artificial intelligence and robotics to sharing platforms and the Internet of Things. This dynamic environment is often addressed with the acronym VUCA which stands for volatility, uncertainty, complexity and ambiguity. In a world where the environment is defined as volatile, uncertain, complex and ambiguous, making strategic decisions becomes increasingly challenging, since the speed of change can lead long-term decisions to become inefficient. Moreover, in a VUCA environment, managers can no longer make strategic decisions on past experience and knowledge. In light of this, the authors of this paper aim to investigate whether Machine Learning and Big Data could be the answer to making strategic decisions in a VUCA environment by answering two research questions. As such, the overall purpose of this study is to provide an analysis of different articles in order to understand the role and use of Machine Learning and Big Data for strategic decisions in the VUCA environment. To this end, the authors conducted a literature review on the areas addressed in the thesis, in order to give a thorough explanation of each theory. The authors also applied a meta analysis on 44 found articles that examine the use of Machine Learning and Big Data in different organizations' strategic decisions. The literature review resulted in the authors finding five major functions in which Machine Learning and Big Data are used in conjunction to guide strategic decisions. After analyzing and discussing these, the authors conclude that strategic decisions using Machine Learning and Big Data are suitable for the VUCA environment, as it leads to quicker decision making which facilitates agility in the organization. Furthemore, the authors argue that BD and ML's role is to lead the organization to enhance its predictability, decrease costs, lower human bias, and improve top management performance. This is followed by the authors addressing how Machine Learning and Big Data is used by organizations in their strategic decisions and ends with suggestions on further research into these rather intricate elements.

Keywords: Strategic decisions, VUCA, volatility, uncertainty, complexity, ambiguity, Machine Learning, Big Data.

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1. Introduction

This chapter presents the thesis's topic and provides an overview of the related terminologies. The current background is raised and the problem is discussed with the research gap. Moreover, a quick summary of the importance of Machine Learning, Big Data and Strategic Decision and the research questions are highlighted. The Introduction chapter ends with the purpose and limitations of the thesis.

1.1. Background

The world is growing more and more complex, uncertain, and unpredictable; where concepts such as Internet of Things (IoT), social media and digital business platforms are the fuel for complexity through hyper-connections among human actors, processes, and organizations (McKelvey, Tanriverdi and Yoo, 2016). This increasingly dynamic environment of uncertainty and turbulence is often addressed with the acronym VUCA - volatility, uncertainty, complexity and ambiguity.

VUCA defines the fundamental internal and external conditions and situations that affect an organization. Social scientists and researchers at the U.S. Army War College introduced the acronym "VUCA" to describe the environment in which their students would need to operate in the future (Baran and Woznyj, 2020). Since then, the concept has been adopted throughout businesses and organizations in many industries and sectors to guide leadership and strategy planning. The four terms volatility, uncertainty, complexity and ambiguity describe the nature of the VUCA environment in which organizations have to act now and in the future (Bennet and Lemoine, 2014). A reason as to why the concept has gained widespread recognition lately is the digital transformation that is taking place; technological advancements in artificial intelligence, robotics, sharing platforms and the Internet of Things are fundamentally altering business models and industries (Bawany, 2016). Because of the uncertain and complex problems that come with this transformation, it is hard to predict what anything is going to be like since cause-and-effect relationships are increasingly harder to identify in the VUCA environment. Thus, we can no longer respond to the present challenges using the strategies of the past, due to the environment companies do business in are becoming increasingly volatile, uncertain, complex and ambiguous (Caredda, 2020). One area that is affected by this dynamic environment is that of strategic decision-making. This is because in a world where we can neither identify cause and effect nor base a decision on past experiences and know-how, making a strategic decision becomes increasingly harder to motivate and achieve. Therefore, organizations need to develop new skills and competencies to successfully adapt to new realities when making decisions in a disruptive VUCA world. The competencies needed to combat the challenges of volatility, uncertainty, complexity and not knowing what to do under these elements, could be that of using Machine Learning (ML) and Big Data (BD), two areas that are evolving every day. We will address ML and BD in our literature review, giving a thorough explanation of key concepts, premises and promises: however, here comes a short introduction to both areas.

Almost all parts of our life nowadays are, to some extent, being changed by ML and BD. For example, Google knows what its users want to know based on the historical searches while Netflix recognizes what movies its subscribers like to watch based on their previous watched movies. Similarly, ML and BD have infiltrated into organizations' various processes to strengthen and support the organizational decision-making processes in a new world typically described by uncertainty and complexity. With the capacity to process substantial computational information and an analytical approach, ML and BD can increase executives' knowledge when handling and addressing uncertainty and complexity and provide a more comprehensive and intuitive approach in the process of decision-making. ML is a part of artificial intelligence that is applied to discover and obtain knowledge from a vast amount of data in order to make a better decision (Saidulu and Sasikala, 2017). BD starts with large-volume, independent sources, heterogeneous with decentralized control, and attempts to examine complex relations among the data (Wu, Zhu, and Ding, 2013).

1.2. Problem Discussion

As stated, one of the main challenges for organizations in today's world is making strategic decisions against a dynamic backdrop. Strategic decisions in accordance with Fisher, Wisneski, and Bakker (2020) are related to indicate and handle a variety of strategic opportunities and challenges facing a business. It is the center of interest for managers at different organization's levels. Strategic decisions demand two main skills: communicating suggestions (easy to perceive, brief but comprehensive, and compelling) and analytical thinking (applying a structured and creative model to functioning through opportunities and challenges). Another indicator of a decision being strategic is that it is long-term and affects how the company moves forward, and therefore is "important in terms of the actions taken, resources committed, or the precedent set" (Eisenhardt and Zbaracki, 1992).

The components of VUCA have different effects on the strategic decisions made in various levels of the organization. The first part, volatility, entails that change is constant and unpredictable, since it does not imitate previous experiences to draw from historical best practices, forcing leaders to forego their past knowledge when discerning future decisions (Codreanu, 2016). As a result of this accelerated cycling of unpredicted change, organizations have an increasing need for fast decision making and the need to move from reactive to proactive decision making (Bradley, Loucks, Macaulay, Noronha and Wade, 2015). The next part, uncertainty, impacts executives' capabilities to discover risks and problems facing their companies, due to a lack of clarity in the environment (Kail, 2010). The uncertainty leads to there being no concrete trends or patterns for a phenomenon, making it increasingly difficult to establish what will happen next and base decisions on it. Next component is complexity, which refers to "…the many connected events that result in randomness and unpredictability rather than certainty" (Paparone and Topic, 2011). In other words, there are numerous issues with uncertain and unstable potential outcomes, which results in very complex and uncertain conclusions during the decision-making process (Siggelkow and Rivkin, 2005). Thus, knowing which strategic decision is most optimal becomes very difficult with the existence of complexity. The last part, ambiguity, refers to incomplete and mixed interpretations of information, and arises due to the lack of models to explain an observed phenomenon (Bolman and Deal, 2017). When executives lack key information of an occurrence in addition to having mixed interpretations of said information, looking for solutions and making strategic decisions becomes close to impossible.

This uncertain and rapidly changing environment of VUCA can lead to the thought of having a two-year strategy, let alone a five or 10-year strategy, feel like an alien concept. As new opportunities and challenges present themselves, the best strategies of the past become obsolete. The problem that arises due to this, is that without a clear vision of the future, and a strategy to take them there, organizations' survival is put at risk (Caredda, 2020). Even though it is near impossible to know what is in store for tomorrow, organizations need to plan for it now, in order to secure a sustainable future. Hence, the action of using effective computational algorithms such as ML is important to promote the “future consciousness” process. Recently, ML has proven its superlative ability to recognize patterns and forecast results for various datasets regardless of the field (Nieto et al., 2019). According to Lounis, Gayed, and Boukadoum (2011), ML's fundamental power is that they construct techniques that can be incorporated into the process of decision making.

As stated before, the VUCA environment has impacted the strategic decisions made in various levels of the organization, since managers can no longer base their decisions on past experiences and knowledge, due to the increasing uncertainty and complexity the VUCA environment brings to the table. In addition, the volatility and ambiguity impact the strategic decisions, as the speed of change from the volatility and the unknown from ambiguity can lead to any long-term decision becoming ineffectual. This led the authors of this thesis to investigate whether BD and ML could be the answer to making strategic decisions under VUCA circumstances, fulfilling an existing research gap by answering the following research questions:

1.3. Research Questions

- *What are the roles of Machine Learning and Big Data in strategic decisions?*
- *How do organizations apply BD and ML in their strategic decisions?*

1.4. Significance of the Study

The significance of this thesis could be of high importance for the top management in organizations. To some extent, it could help with understanding the role and importance of Machine Learning and Big Data in strategic decisions. Secondly, this thesis sets a platform for future researchers who consider Big Data and Machine Learning an important fraction of the business’s strategic decision in order to have a competitive edge. Thirdly, this thesis will also summarize the existing theory and articles related to the importance of Machine Learning and Big Data in strategic decisions by analyzing different articles. Finally, this thesis will be useful for future researchers as they could benefit from the findings and the discussion of the articles and could further discuss the research problem from a different perspective.

1.5. Purpose

The overall purpose of this study is to provide an analysis of different articles in order to understand the role and use of ML and BD for strategic decisions in the VUCA environment.

1.6. Limitations

Considering the time limitation and the broad area of the research area, the authors of this study were limited to the following points:

- This thesis is limited to the findings of existing theory and articles that are published before 29th of October 2020. Therefore, articles published after this date are not included.
- This thesis is limited to the findings of existing theory and articles that are published after 1988. The reasoning being that ML and BD were not common before this date.
- The authors used only articles that are published in authorised and peer-reviewed journals.

2. Methodology

This chapter further presents how and why the authors chose to investigate the chosen issue and illustrates how the existing literature review was carried out. This is followed by explaining how the research itself was done, in order to give a thorough explanation to the reader. The chapter ends with a discussion on the quality of the study and the disposition of the thesis.

2.1. Review of existing literature

As we decided at an early stage to address and analyze how strategic decisions are made in a VUCA environment, and the fact that several authors have indicated the need for new decision-making ways, we started to look for new solutions to making decisions under the mentioned circumstance. After a brief review of new techniques and technologies that have come to be used in strategic decision-making, we found studies and articles examining the usage of BD when collecting information to base their decisions on. After reading these we found that BD is very much in use during organizations' decision-making process, however, as it only helped with the collection of information and not the final decision itself, we concluded that we needed another element to guide the strategic decisions.

To this end, we looked in the articles references' list and searched for the authors of said articles, finally coming across the use of ML in conjunction with BD when making strategic decisions. Thus, we decided to do a meta-study on empirical studies that addressed BD, ML and VUCA for strategic decision-making. However, as these theories are rather intricate in nature, we concluded that we needed a thorough literature review to ensure that each theory is written in a comprehensible and appropriate manner. Consequently, we decided to use LUBsearch and Google Scholar to look for articles explaining VUCA, strategic decisions, BD and ML, both in conjunction with each other and by themselves.

Furthermore, we wanted to anchor the thesis to the course being studied, Strategic thinking, and therefore decided to include a piece of literature discussed during the course, namely Julia Sloan's book Learning to Think Strategically (Sloan, 2019). We chose to include this book in the literature review first and foremost because of it being a major source of information during the course, explaining new ways of making strategy while also giving a hefty background on strategic decisions. Another reason is that it highlights the use of intuition during strategic decisions, which is one of the more recent paradigms and explains the connections in an understandable manner by giving examples and scenarios where intuition is used.

2.2. Data collection

In order to collect the data needed to address whether BD and ML could be a solution to making strategic decisions in a VUCA context, we used LUBSearch search-engine to find relevant articles, dissertations, studies etc., in order to make sure all articles were peer-reviewed. Using the advanced search, we first decided to look for articles containing VUCA, as it has a focal point in this thesis. However, after a couple of searches, especially when including the other key areas addressed in the thesis, the result of the searches was too low, eventually ending in zero findings. Thus, for us to find any valid data, we decided to forego the use of VUCA in our search and instead focus on the other elements, namely that of decisions, BD and ML. The first few searches gave an enormous number of results: hence we decided to be more specific in our search, eventually searching for Strategic Decision Making AND Big Data AND Machine Learning, which resulted in 42 articles.

However, after discussing the number of articles found during this search query with our supervisor, we concluded that we needed a higher result since some of them would inevitably be dismissed after reading them, and thus make the basis of our thesis too small. Having this thought in mind, we wanted to have a result between 100-200 articles to ensure that the basis would still be big enough after a first readthrough, yet small enough for us to read through them in a reasonable amount of time. After a few conversations, we decided to search for Strategic* AND Big Data AND Machine Learning, finally fulfilling our aim with 121 articles on the 29th of October. After going through all 121 articles and reading their abstract, this number ended up to 42 articles, due to the rest having low relevance to the study and/or missing certain parts needed for the purpose. For example, as we decided to include Strategic* in our search not every article found had to do with strategic decisions. Instead, some investigated strategic leadership and strategic marketing etc. Another example of articles having low relevance was that some only incorporated all three areas in their abstract and not giving any significant room for them in their analysis, instead focusing on either one of them and not all in conjunction with each other.

Moreover, some articles were not applicable in the thesis, as they sometimes were from conferences, discussions, etc. Therefore, they did not have any real findings, rather being high-educated guesses about the use of BD and ML in strategic decisions. The 42 articles found were all read through followed by us making summaries of each and everyone. After comparing the summaries and analyzing what the articles' aim, execution and conclusion were, three articles were dismissed due to an inadequate connection to strategic decisions. However, after reading through the references list of the remaining articles, five additional articles of relevance were found and therefore added, resulting in 44 articles making up the basis for our research.

Frequency Table of searches		
Search terms	Date of search	Result
VUCA AND Decisions	27/10	77
VUCA AND Strategic Decisions	27/10	16
VUCA AND Decisions AND Big Data	27/10	2
VUCA AND Decision Making AND Big Data	27/10	2
VUCA AND Strategic Decisions AND Big Data	27/10	0
VUCA AND Strategic Decisions AND Machine Learning	27/10	0
Decisions AND Big Data AND Machine Learning	28/10	2971
Decision Making AND Big Data AND Machine Learning	28/10	1222
Strategic Decisions AND Big Data AND Machine Learning	28/10	76
Strategic Decision Making AND Big Data AND Machine Learning	28/10	42
Strategic* AND Big Data AND Machine Learning	29/10	121

2.3. Data analysis

The 44 articles we decided on were all read through again in order to find major business functions that apply ML for their BD in order to help managers with their strategic decisions. The reason we decided to base the topics on major business functions is because of the limited use of ML and BD for strategic decisions. Because of this, we were not able to find specific organizations using it nor could we find general industries applying it for their strategic decisions. However, early on we did find that specific business functions, such as Finance and Marketing, use ML and BD for strategic decisions quite frequently, and thus decided to look for more functions and common denominators therein. This resulted in five major business functions: Finance, Healthcare, Government, Marketing and IT. The process of finding these topics to base the analysis on was therefore an iterative process and in no form was it determined before-hand, rather made up as we went through all the data several times in order to find key-takeaways of the articles. The reason why Government was included as a business function is partly due to the fact that various government departments are highly affected by the VUCA environment, and also because of the widespread use of BD and ML in their strategic decisions. Thus, even if government is not a business function per se, its different departments are very much alike the other business functions listed in the thesis. Also, the Covid-19 pandemic have shown how different governments handle new and dynamic circumstances, thus by including governments in the thesis, we hope to provide a better understanding of how BD and ML can combat VUCA on a global scale.

This iterative process was helpful because it let us think outside the box and not be tied to a specific line of thinking or method, which allowed us to be creative in dealing with the analysis and potential problems. Another advantage of this process is that, due to the limited use of BD and ML for strategic decisions, we did not know whether we would find any valuable insights during the analysis. Hence, by going back and forth when working with the material, we were able to adapt to the situation and come up with novel solutions when sifting through the data. However, a negative aspect of this process is that we did not have formal procedure, which at times made it hard for us to know what to do with the material we found. In addition to this, the lack of a formal procedure also put a greater pressure on us to give a detailed description of how we conducted the research, which is often easier when you have an acknowledged method. The iterative process was also a contributor to us deciding to use the topics we did. In hindsight, we are satisfied with the outcome of these topics, however, we do wish that we were able to find more generalizable topics, such as different organizations and industries, in order to make the thesis more applicable and significant for businesses.

Furthermore, in the Findings chapter we provide a table that classify these major business functions where ML and BD are used for strategic decisions, which ML techniques that are used to this end, and the reference to the articles addressing each technique. This was done in order to create an overview and, therefore, make it easier for us and the readers to understand which technique is used for which strategic application, for the strategic decision to take place. The Findings Table also makes up the basis of the discussion, where we found major business functions where BD and ML are used to make strategic decisions, based on the definition used in this thesis. The articles found, that highlights how BD and ML are used in the strategic decisions, will be analyzed through the lens of the chosen theories in the literature review, to make sure that no relevant information is lost. Hence, VUCA and Strategic decisions will be applied to the findings made in the articles.

2.4. Research quality

As we have limited our thesis to be solely based on scholarly (peer-reviewed) articles, the material found is of high quality. However, as the current use of ML and BD in organizations' strategic decision making is rather limited, the findings made in the thesis are similarly limited. Thus, the analysis, discussion and conclusions that are made are restricted to the business context they are in and not over industries as a whole, which impacts the significance of the study as well as the quality of the conclusion. The limited use of ML and BD in strategic decisions, however, is something we were aware of when we started the research and seeing as we aim to highlight the current situation, this impact was tolerable. Another limitation to the quality of our research is the fact that during the data collection we had to forego the use of VUCA in our searches, due to there not being any articles containing the word. The result of this was that we ourselves had to find information on VUCA, and after that apply our definition on the findings, which sets up for a subjective analysis and discussion. For example, had we gone with another definition, the conclusions of the thesis could be different: hence the replicability of the study is lessened.

The same applies to our definition of strategic decisions, as in, had we defined it differently we would most likely wound up with different business functions and thus a different result. The replicability is further impacted negatively due to us coming up with our own type of study and methodology, which have been a work-in-progress, deciding what to do and how to do it along the way. To address this, we made sure to explain everything we did as comprehensively and cohesively as possible in our methodology, thus lessening the negative impact on the replicability. Another element that may have influenced the research quality is the fact that we only used the LUBsearch search engine while collecting our data. Had we for example used another search engine, such as Scopus or ResearchGate, our findings could be richer in both quality and quantity, and thus resulted in a more profound conclusion. However, when we carried out our data collection, bearing in mind that some articles would inevitably contain more data in their references' list, we concluded that the result of 121 articles would be sufficient to answer the research questions asked in this thesis. Thus, we decided that we did not need to use another search engine.

3. Literature Background

The background and the research questions of this thesis were set in the previous chapter. In this chapter the authors will provide a background of the existing literature related to the main concept used in this thesis such as: VUCA, BD, ML and Strategic Decisions, where different articles, databases, journals, and authoritative websites are referenced in order to write the Literature Review chapter.

3.1. The VUCA World

VUCA defines the fundamental internal and external conditions and situations that affect an organization, and is an acronym which stands for volatility, uncertainty, complexity, and ambiguity. Social scientists and researchers at the U.S. Army War College introduced the acronym "VUCA" to describe the environment in which their students would need to operate in the future (Baran et al, 2020).

Volatility: Refers to the speed, volume, nature, magnitude of a phenomenon that may or may not be in a pattern form, it is liable to change rapidly and unpredictably. The more volatility phenomenon is, the more complexity we have. A complex and volatile system can be changed from one state to another very quickly. On the other hand, in systematically volatile environments change is constant. The strategy needs to evolve from resisting it to working with it through agility and enabling adaptive capacity, (Giones, Brem, and Berger, 2019).

Uncertainty: The inability to know everything fully, uncertainty occurs when there are no concrete trends or patterns for a phenomenon which makes it difficult to establish what will happen next and base decisions on it. It refers also to the lack of predictability, the prospects for surprise, and the sense of awareness and understanding of issues and events. Uncertainty comes from many elements with nonlinear interactions. The strategy needs to be shifted from creating an optimal strategy that is related to one environment in the future, to developing organizations that can operate under multiple outcomes by increasing diversity.

Complexity: According to Giones, Brem, and Berger (2019), the world is an interconnected system straining under the burden of its own complexity. Complexity refers to many parts being interconnected and interdependent. In other words, there are numerous issues with uncertain and unstable potential outcomes, which results in very complex and uncertain conclusions when making a decision.

Ambiguity: It results in the haziness of reality and the potential for misreading. When environments become more complex, simple linear cause and effect descriptions break down. Ambiguity arises due to the lack of models to explain the observed phenomena. Resolving ambiguity means understanding the context within which the event takes place. It requires a strategy of system thinking to see the interconnections and gain different perspectives in order to build up the full context within which an event can be properly understood. In other words, the quality of being open to more than one interpretation.

In a world characterized as being VUCA, the real challenge is to create agile organizations that can rapidly adapt to changes in the business environment (Sattar, 2016). Whereas in the past senior executives were able to use their experience and knowledge to solve an issue or a new situation that surfaced, in the VUCA environment this is no longer feasible. This is because the information that characterizes an occurrence is incomplete and all the decision variants do not display significant differences, so it is not possible to determine which option will offer the company the most benefits. Moreover, in the VUCA setting, making strategic decisions is increasingly harder as the decision itself can trigger chain changes in the whole organization, due to the volatility and ambiguity that exists within the environment. In addition to this, whereas before the managers' decisions were made under conditions of certainty, in this dynamic and uncertain setting such decisions must be taken without any further thorough processing of information, which can have a negative effect on the execution of the company's strategy (Minciu, Berar and Dobrea, 2020). Hence, a new way of making strategic decisions is needed.

A way to combat these four elements of VUCA is by developing agility, which is defined as the capability of an individual, team or organization to quickly sense and react to sudden change (Baran et al, 2020). At the level of the *individual person*, agility includes what Pulakos, et al (2000) introduced “adaptive performance” which includes qualifications and skills such as learning new technologies or tools, handling crises or emergencies, coping effectively with stress, among others. For *teams and groups*, agility often includes a mix of a quick understanding and making sense of new situations along with standards that support strong interaction and dissent to boost and raise the quality of decision-making (Baran et al, 2020). For *organizations*, agility includes ongoing understanding and monitoring of the environment and of the organization's stakeholders to reveal and react quickly to weak signals of threats or opportunities, Baran, et al (2020). In their study, Baran et al (2020) highlights the value of implementing training and development to promote agile behavior, where their data indicate the importance of using training to build both skills and expertise among staff and leaders that can facilitate or allow change and, consequently, organizational agility. One of the behaviors they highlight that would promote agility in the organizations is that of fast decisions, as it is of high importance to rapidly respond and adapt to fast-changing situations. They argue that slow decision making impedes organizations' agility and adaptability, because as senior executives consider how to react to one change in the environment, other changes are probably happening at the same time.

3.2. Strategic Decisions

Every organization that has ever existed has at one point or another made a decision based on information that affects the company. The process of coming up with this decision can easily be seen as just making a choice, which is far from the reality of strategic decision-making. In general terms, decision-making is a systematic process which starts off with the identification of either a problem and/or need for the organization and ends with applying a chosen alternative to address this need or problem (Alkhafaji, 2011). Moreover, strategic decision-making also consists of evaluating numerous potential solutions, which is then followed by selecting the best out of these alternatives. Another indicator of a decision being strategic is that it is long-term and affects how the company moves forward, and therefore is "important in terms of the actions taken, resources committed, or the precedent set" (Eisenhardt and Zbaracki, 1992). As such, strategic decisions have major resource propositions for businesses and involve the possession of new resources and the organizing or reallocating of current resources. Therefore, strategic decisions are by nature high-risk decisions, meaning that if an organization makes the wrong strategic decision today, they could live with the consequences for an extended time. Furthermore, according to Fisher, Wisneski, and Bakker (2020), strategic decisions are related to indicate and handle a variety of strategic opportunities and challenges facing a business. It is the center of interest for managers at different organization's levels. Strategic decisions demand two main skills: communicating suggestions (easy to perceive, brief but comprehensive, and compelling) and analytical thinking (applying a structured and creative model to functioning through opportunities and challenges).

As strategic decision-making has been a part of organizations for a long time, it has been subjected to different paradigms and evolutions throughout the years, each contributing to the next one. The most acknowledged ones are that of rational, limited rational and intuitive decision making. To understand these different paradigms and what they entail, the literature review on strategic decision making will be divided into three sections: (i) rational approaches (ii) limited-rational approaches (ii) intuitive approaches.

3.2.1. Rational approaches

Two of the early paradigms in decision making were the rational choice paradigm and the bounded rationality paradigm. In rational choice, a decision is defined as a cost-benefit maximization process where the decision makers know their objectives, classifying these depending on their priorities (Simon, 1979). Moreover, they know all potential options and can therefore choose the solutions that maximize their utility. According to Oliveira (2007), rationality has been defined as the "compatibility between choice and value." Rational behavior therefore seeks to heighten the significance of the consequences focusing on the process of choosing rather than emphasizing the selected alternative. In rational decision-making models, decision makers evaluate several possible substitutions from different possible situations before selecting a choice (Oliveira 2007). These possible situations or scenarios are weighted by probabilities, and decision makers can determine the expected result for each choice. The final choice that the decision maker chooses would be the one offering the best-predictable consequence and with the highest prospects of consequence (Oliveira 2007). Rational decision making may involve several different processes. Regardless of the various steps in each process, rational decision processes have similarities that mostly result in effective solutions. A model of rational decision-making is presented in the following steps:

1. Identifying the problem that requires a solution.
2. Identifying the solution scenario.
3. Carrying out a gap analysis.
4. Gathering facts, options, and alternatives.
5. Analyzing option outcomes.
6. Selecting the best possible options.
7. Implementing decisions for the solution and evaluating the final outcome.

3.2.2. Limited-rational approaches

In bounded rationality, the assumption is that decision makers' rationality is insufficient due to factors such as information available, personal limits, the time available to make decisions, etc. (Simon, 1979). Also, in bounded rationality, the decision maker does not necessarily know all potential options. Thus, they cannot choose the solution that maximizes their utility, instead choosing the most satisfying one among the available alternatives.

There are two schools of thought in linkage to bounded rationality, the analyst and the experiential schools. Both schools consist of a three-step model for decision-making: (i) problem definition; (ii) identification, evaluation and selection of alternatives; (iii) implementation alternative (Simon, 2019). The difference between the schools, however, is that they emphasize the single steps differently. Whereas the analytic school prioritizes the two first steps and considers the last one simply as the execution of the selected alternatives, the experiential school values the implementation alternative step more than the others.

From these schools, different decision-making theories were developed, where each and every one has contributed to defining different features of more recent decision-making processes. One that has had a lasting effect and shifted the focus from decision-making towards that of the decision-maker is Keen and Scott Morton's individual differences perspective theory (1978). They were among the first authors to highlight the importance of each decision maker's personality when it comes to making decisions. They stated that a unique and standard decision-making process does not exist as it is influenced by subjectivity. Thus, decision-making is strictly linked to the decision-maker 's experience and intuition rather than on rational choices.

Recently, this focus on decision-makers instead of the decision making has become increasingly relevant, where factors such as experience and intuition are held high. This leads us to the next section, intuitive approaches, where we will explain newer decision-making processes that are based on the decision-maker's personality, and why.

3.2.3. Intuitive approaches

According to Sloan (2019), the classic approaches to strategic planning stems from the technical rational scientific school of thought, and highlights in some form the traditional six-step model of decision-making:

Analyze the problem ⇓

List alternatives ⇓

Evaluate alternatives against a set of criteria ⇓

Weight each criterion ⇓

Rate each option on each criterion ⇓

Sum it up – Compare – Voilà!

This way of illustrating how to make a decision is reassuring for many, as it is rather straightforward, systematic, methodical, rational and based on good analysis. As the steps in themselves are easy to understand and follow, the model also allows the user of it to explain and justify why they decided as they did to others. However, Sloan highlights that this sense of assurance, that if one follows the steps the decision that is eventually made is optimal, is false. The reason for this is that the model does not consider the complexity that may surface, as it overlooks the messy parts of the complex problem-solving process. These messy and nonlinear elements are essential to distinguish strategic thinking from strategic planning, and allows for strategic innovation, adaptability and sustainability to be at the forefront.

To accommodate these complex strategic decisions that may arise, Sloan (2019) suggests that strategists need a combination of cognitions that incorporates what she calls critically reflective processes. These processes make sure that strategists challenge their own underlying assumptions about a specific strategic issue, hence allowing them to examine and explore the problem at hand fully. One of these processes, called reflection in action, is when a strategist reflects in and on his actions during the decision-making process. This reflection can take place in many stages and forms, from reflecting on the kinds of factors, variables, and patterns before him, to the multitude of underlying frames, assumptions, and belief systems that he brings to his reflections. This in itself is a very complex process for many: however, among successful strategists this is commonplace and is often the defining trait of their success thanks to the influence it has on complex decision-making. Sloans (2019) final remark is that even though strategists' judgments must be grounded in relevant data, they should also be open to reevaluating their conclusions, and willing to battle confusion and uncertainties when engaging in critical reflection on action and decision-making.

In the other approach, the integrated strategic decision making, Sloan (2019) highlights the use of intuition and rationality to strengthen strategic thinking and therefore the decision making. Critical reflection once again plays a part, this time as a tool to integrate intuition and rationality effectively in strategic decision making. The reason why intuition is desirable during decision-making is that it helps decision makers determine where to focus their attention and helps them to recognize problems and sort them, by leveraging their experience and knowledge in a non-analytical and discreet manner. However, this is not enough to make a decision and therefore rationality kicks in, to help clarify and systematically discern issues and opportunities which warrant further consideration. Without rationality, the process of ordering facts in a linear and logical way would become almost impossible.

The result of this is that intuition works to identify possible causes and to verify true causes, followed by rationality which plays the critical role of identifying relevant information and analyzing facts. Hence, both parts are needed to make a well-informed decision. This is apparent in Sloan’s (2019) interviews with executives, who consistently noted that intuition mostly leads their strategic decision making, however, it needs to be countered by rationality to hinder runaway intuition, which can be as detrimental as it can be beneficial.

3.3. Big Data

Roger Magoulas of O'Reilly Media presented the term “Big Data” to the computer environment in 2005, in order to describe a vast volume of data that conventional data management methods cannot handle and analyze due to its complexity and volume of this data. Madden describes BD as: "Data that is too big, too fast, or too hard for existing tools."

“Too big" implies that businesses must gradually deal with data collections on a petabyte volume that arise from click streams, payment history, detectors, and others. "Too fast" implies that the data is not only big, but should be processed rapidly, such as detecting fraud or identifying an ad to be shown. "Too hard" is a term which implies that current tools may not be able to handle such data easily, or that it requires some further analysis which is not suitable for existing tools. BD does not apply to a specific market. Instead, the phrase refers to technologies of data management that have developed over the years. BD helps stakeholders to store, process, and evaluate vast volumes of data in order to obtain powerful insights at the required time and speed, (Hadi, et al., 2015).

The vast volume of data produced enables stakeholders to make any type of decisions at the right time, where costs can be rescued, and processes can be better integrated in both the public and the private sectors. For instance, customer experience and desires can be understood in the retail industry through BD analysis, such as customer interaction in a shop, web browsing, brand scans, and many more. In addition, the United States Healthcare BD World, which involves documentation of over 50 million patients, employs data-driven techniques to identify obstacles in the healthcare sector. Zaslavsky et al. (2013) notes that the queries used to process BD are very complicated.

BD, in accordance with Green et al., (2018), implies that companies will have the power to catch ‘sequential causational operations’ on a real-time basis of a company. BD is the outcome of two movements: decreasing cost of storage and the way of analyzing and interpreting data that have quickly emerged (Green et al., 2018). This type of data is created from emails, online transactions, audios, videos, images, streams, posts, logs, search queries, social networking interrelationships, health records, data from science, different sensors and phones' applications

(Zikopoulos and Eaton, 2011; Schneider, 2012). They are saved in databases and grow on a vast scale where they become hard to catch, form, save, share, control, analyze, test and visualize via specific database applications. BD has different operational definitions. It characterizes the activities and information systems that collect, restore, and check the massive amounts of data. BD is also defined as, ". . . large, dynamic, and various volumes of data being generated by machines, tools, and people" (Ernst and Young Global Limited, 2014).

Business analytics and BD are now spread throughout almost all parts of major firms' business strategies and decision-making. For example, a large U.S. firm might analyze a billion data elements daily in order to interpret its competitive environment (Griffin and Wright, 2015). In 2012, a global project was achieved, called "The Human Face of Big Data", which built on timely gathering, imagining and analyzing a big volume of data and many statistics were obtained. Facebook, for example, has 955 million active accounts every month who are using 70 different languages, upload 140 billion photos, the friend connections reach 125 billion, a daily amount of 30 billion pieces of content and 2.7 billion comments and likes have been posted. 48 video hours are uploaded every minute and 4 billion views performed on YouTube every day. Twitter has 1 billion tweets from 140 million users every 72 hours. Every minute, there are 571 new websites. In the coming years, these numbers will increase by 50 times (Tankard, 2012).

In order to differentiate between data and BD, BD is characterized by three features, the massive amount of produced data (Volume), the higher pace of producing data (Velocity) and different sources from where the data is gathered from (Variety). The three Vs of BD (volume, velocity, and variety) shape an overall definition for the BD, and they break the story that BD is only about the amount of data. Furthermore, every one of these three has its own offshoots. (Figure 1 below).

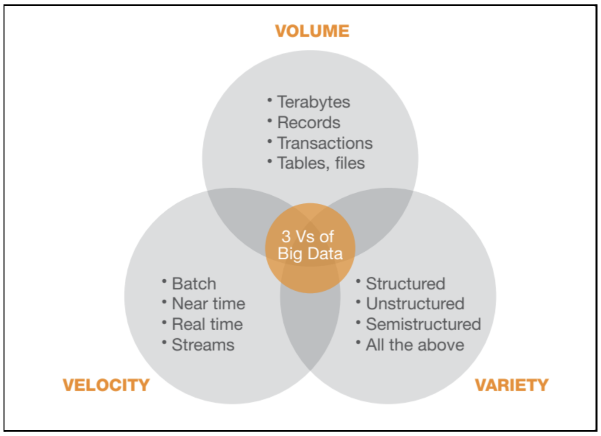

Figure (1): The three Vs of BD

The volume of data is an essential feature for BD. People define BD in terabytes. Still, BD can also be measured by the number of transactions, records, files, or tables. Some companies find it helpful to count BD in the form of time. For example, due to the seven-year statute of limitations, many companies would like to keep seven years of data related to risk, legal analysis, and compliance available.

According to Russom (2011), BD used to be a technical problem, but now it is a business opportunity. Big data comes from a great diversity of sources and roots and, in most cases, BD is categorized into three different types: structured data, semi-structured data and unstructured data. Structured data are queried, recalled, analyzed, tagged data, controlled by a machine and can be sorted and entered a database easily. Unstructured data are random data, described by its difficulty to analyze. Semi-structured data does not adjust to specific fields but includes tags and labels to break down elements of the data (Zikopoulos and Eaton, 2011; Russom, 2011).

Today, companies are discussing BD to find and discover information they did not recognize before. It is an important mission since the recent economic recession forced a deep change into most businesses, particularly those that depend on a large number of customers. Companies can study and investigate BD by using analytics in order to understand the current situation of the company and track their customer behavior, (Russom, 2011).

3.4. Machine Learning

Machine Learning (ML) is the examination of computer algorithms that, over practice, improves automatically from observations of facts and events without direct programming. It is seen as an artificial intelligence (AI) sub-set method. ML usually tries to focus on building programs for computers which can provide access data and use that in order to learn on its own. In general, this series of actions begins with data or observations, such as instructions and examples, in order to find trends in the data and make a better conclusion. The key goal is to give a permission for the systems to be able to learn in the absence of human intervention or help and to adjust its work and action in a way that is appropriate to the specific circumstances. Different phases are involved during the time of working with ML such as: gathering data, preparing these data, selecting a pattern or a model, practicing, valuation, hyperparameter tuning, and prediction.

ML provides different methods in order to learn from the given data and information. Usually, it relies on the predicted results, and the shape of what is put in and received. ML algorithms are arranged in classes and categorized according to the pattern of learning. ML methods and techniques can be categorized into four different groups that contain the next techniques (Saravanan and Sujatha, 2018; Jain, Murty and Flynn, 1999; Dutton and Conroy, 1997).

- Supervised ML: Finding designs and patterns to improve predicted models using both input and output data. Supervised ML is one of the most common MLs, and maps an input to an output established as an input-output set. Supervised ML will be discussed separately in the next part.
- Unsupervised ML: Obtain designs and patterns from a known and given dataset with the absence of any labeled outcomes or reference. This technique is considered as a detecting, discovering and identifying design/pattern in the input data, and is suitable when no information is known based on desired outcomes (Ghahramani, 2003).
- Semi-supervised ML: Located between unsupervised and supervised ML techniques within the training stage; semi-supervised ML uses both labeled and unlabeled data. It considers a minimal volume of labeled data and a big volume of unlabeled data in order to build a better classification model (Zhu, 2005).

- Reinforcement ML: Consider the appropriate process action in a specific status or case in order to maximize the results. Reinforcement ML is applied by various software and applications.

Supervised Machine Learning

Supervised ML is the process of searching and finding algorithms from the outer surface or structure in order to provide general hypotheses, which later makes predictions and forecasts related to the future patterns (Kotsiantis, Zaharakis, and Pintelas, 2007). Supervised ML algorithms mostly discover relationships, insights, and examples from a composed labeled training set and information. An ML algorithm has the right answers for a problem within the training stage. In this way, an ML algorithm learns itself how the other characteristics and historical data are participated in the main target, allowing judgments for an accurate forecast of future activities. The types of supervised learning techniques are:

- Regression: The algorithm outcomes for each case is a statistical target, for example, how much the income of a new marketing strategy would result in. Regression handles separate and distinct results.
- Classification: The algorithm attempts to label each of the outcomes by selecting between two different categories. The process of selecting between two classes is named a binary identification (or multi-class classification), for example, the select between if someone will face a default on a requested loan or not.

3.4.1. Machine Learning in Business Big Data

The mechanism of identifying interesting trends in databases of BD that are useful in decision-making is called data mining, also known as "knowledge discovery in databases" (Fayyad et al., 1996). Data mining is a field of increasing interest and an area of application that can provide a company with a competitive advantage by leveraging the capacity of BD warehouses (Bose and Mahapatra, 2001).

The role of identifying trends and patterns in BD of a business is not new. Historically it has been the job of market analysts, who typically use statistical methods. However, the spectrum of this operation has recently shifted. Big electronic databases that store business transactions have been generated by the widespread use of computers and networking technologies. Via their point-of-sale terminals, retailers, including Wal-Mart stores, collect millions of sales transactions (Bose and Mahapatra, 2001). To determine purchasing patterns of individual customers as well as customer groups, and sales patterns of various stores, transactions can be analyzed.

Intense competition drives businesses to find new ways to gain and grow market share while lowering costs. The efficiency of target marketing practices can be increased by a greater appreciation of consumers' purchasing behavior. Data warehousing technology has helped businesses to manage and store BD in a way that can be processed and fully developed. The area of "artificial intelligence" has generated a range of ML techniques that are valuable in automating repetitive and discovering different activities patterns, (Bose and Mahapatra, 2001).

These factors have altered the way business's BD is analyzed and greatly contributed to data mining, which combines ML techniques with the business analyst's intuition, in order to discover important patterns of business's BD. Data mining is a complicated process and requires different iterative steps. Figure (2) provides an overview of this process.

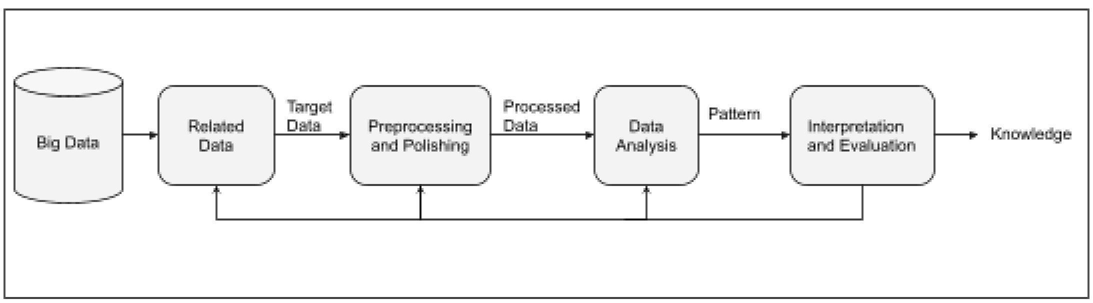

Figure (2): An Overview of Data Mining Process; Source: Fayyad et al., (1996)

The data selection for analysis is the first step. Historical data is usually used. The set of data may be extracted from a particular source of the BD, such as a data of a warehouse unit, or may be extracted from many other systems. Then the related data chosen begins with the Preprocessing and Polishing processes. When data is extracted from different databases, the lack of consistency across these BD leads to negative consequences such as bias in effect estimates (Gøtzsche et al., 2007; Tendal et al., 2009; Jones et al., 2005) and bias assessment risk (da Costa et al., 2017). The polishing operation eliminates negative consequences and discrepancies. In order to enhance the accuracy, ML's techniques require the data to be preprocessed. Some include the conversion of information from one scale to another, the detection of BD's predictive characteristics, and the elimination of the given data's dimension by recomposition.

To define patterns, i.e., formulas that reflect data relationships, the data set is analyzed after the Preprocessing and Polishing processes. To ensure the framework's generalizability, the data selected is then evaluated with new data sets. The framework should be converted into implementable strategic plans which are expected to help the company to take any decision. Business understanding becomes a pattern that meets these requirements. The phases of the project of mining are carried out iteratively before relevant market information is obtained and strategic decisions are taken. (Fayyad et al., 1996)

3.4.2. Machine Learning Techniques

ML is the research of computational procedures to optimize the process of information acquisition from samples (Langley and Simon, 1995). In order to remove the costly information, an engineering process is involved in designing the knowledge-based systems. Exploring a pattern in a training sample is a popular approach used. This pattern is then used for the classification and/or forecasting of new examples' behavior. The main groups of ML's techniques are:

- Rule Induction (RI)
- Neural Networks (NN)
- Genetic Algorithms (GAs)
- Case-Based Reasoning (CBR)
- Inductive Logic Programming (ILP)

Rule induction (RI) generates a decision tree or a collection of decision rules from a specified list of training examples (Apté, and Weiss, 1997). All examples in the training dataset are expressed by the root node of a decision tree. If two or more groups correspond to these examples, then the most discriminating characteristic is chosen, and the set is divided into different groups. This characteristic collection and dividing process continues until a unique group of examples is defined by each terminal node. To assess the classification accuracy of the new examples, the generated decision tree is then implemented to a validation sample.

Whenever a decision tree is overfitted to a collection of training samples, its reliability of classification with new information may decrease. In order to remove this overfitting, the tree must be trimmed before it is implemented in a real-world application. Think of a bank seeking to design the delinquency of loan repayments. Training data set for this question would contain records of historically awarded to borrowers. Depending on the repayment performance of the customer, the borrower record is then classified as delinquent or not.

Figure (3) indicates a theoretical decision tree. Depending on a credit rating characteristic, the data collection is divided into two groups. It has been found that those with bad credit ratings fall into the delinquent category. The borrowers with a high credit rating shape a mixed party. Based on the indebtedness feature, the latter is further split into three subclasses/groups. These feature choice and dividing processes remain until a single group of borrowers is held by each leaf node. For classifying new borrowers, the corresponding tree could be used.

It is possible to convert a decision tree into a set of rules. Those rules are usually specified in normal disjunctive form. It is therefore likely to obtain rules directly from the training data sample. The model created by Rule Induction is very promising because it is easy to comprehend. A drawback of a decision tree-based system is that it generates only mutually exclusive groups; therefore, a Rule Induction algorithm can resolve this by establishing rules regarding overlapping groups.

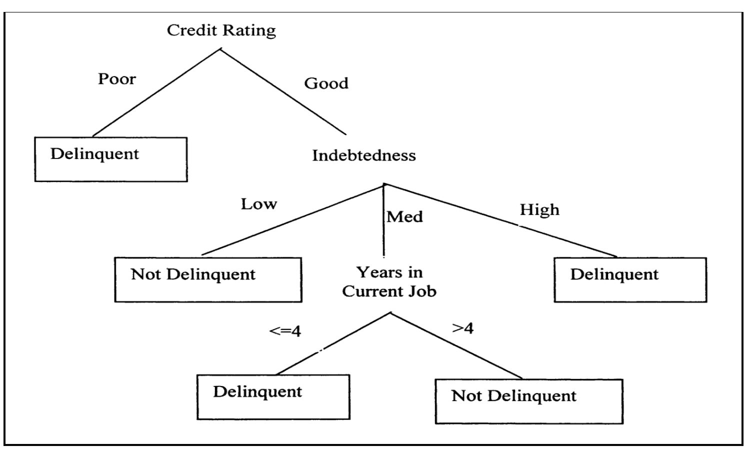

Figure (3): Decision Tree - Source: John and Zhao (1997)

Neural Network (NN) comprises a collection of input nodes that, via a set of hidden nodes, are linked to a collection of output nodes, and thus form a multilayered network (Rumelhart, Widrow and Lehr, 1994). A bias value and an output function are connected with each node. Via input links, the NN collects input signals, calculates an output, and converts it to other nodes. Each link has an essential weight that adjusts the input signals before it is transferred to the node connected to that link.

The input signal to a node is, thus, the sum of weights for all the signals accomplishing it from its input links. As the output element, a sigmoidal function is mostly used. A NN is educated by using established classification examples. By iteratively changing the weights associated with the network links, the network learns the classification model. By iteratively changing the weights associated with the network links, the network learns the classification model. To lessen the impact of overfitting, the educated network is pruned. The importance of a NN is that every classification model can be taught. However, teaching a network takes time as it takes various passes through the training collection. Inside the network topology and the link weights, the classification model in a NN is buried. The classification model is, therefore, not visible to the end-user. Strategies to derive conceptual rules from NNs are developed by researchers [Craven, and Shavlik (1997), Setiono, Thong and Yap (1998)].

The case-based reasoning (CBR) method saves cases in a case-based and utilizes them in the machine learning task (Kolodner, 2014). A case stores a summary of an issue and its treatment, which may be a description of a method or a classification. A CBR framework tries to find a matching case given a new issue. For this reason, the closest neighbor matching algorithm is sometimes used.A solution is given by the corresponding matching case. In the indexing framework and the definition hierarchies correlated with the case-based, the domain interpretation is captured. The benefit of using a CBR technique is that the domain information and knowledge is easily applied to increase the model's effectiveness. The model is, furthermore, very robust, but with noisy or incomplete data, its performance gracefully reduces, and due to the shortage of a supporting tool, maintaining and preserving a large case-base can be challenging (Kolodner, 2014).

Genetic Algorithms (GAs) are a family of regularization techniques based on the idea of natural evolution and selection (Goldberg, 1994). They were utilized in tasks of prediction and classification. In a GA, selection, crossover, and mutation are the three fundamental processes.

The selection process chooses the elements (selected elements) from a data set based on the fitness of an element. Better elements have a higher chance of being chosen due to their greater fitness value. A mating pool is created from these selected elements. The crossover process replaces a portion of an element with another portion from the mating pool in order to generate new elements that are added to the data set. The hunt for any optima continues through the selection and cross processes' sequential applications. To build a new one, the mutation process spontaneously adjusts a portion of an element. In this way, mutation brings diversity to the data set and is sparingly used.

With noisy data, GAs function well. They can be easily linked to other models and other ML methods to build hybrid systems as they use much less domain knowledge. However, it typically takes some work to transform the data mining dilemma into a model that can be expressed by a GA. This is due to the available data which would have to go through transformations so that it has meaning to perform GA processes such as cross-over, reproduction, and mutation on it. This includes some extra work on behalf of a data miner.

Inductive Logic Programming (ILP) utilizes first-level predicate logic to realize a collection of positive and negative instances (Bergadano and Gunetti, 1996). Predicate logic, which is used in ILP systems as the modeling language, offers a clear conceptual explanation mechanism and endows ILP with advantages over attribute-based developing skills. The first advantage, it is simple to express complicated interactions between components, hence improving the model's generalization ability. The second advantage is that domain information in an ILP environment can be easily expressed. This strengthens the system's effectiveness. It is also easy to comprehend the model represented in predicate logic. ILP systems with new examples appear to have poor predictive accuracy and are very susceptible to noise. In the context of spurious data, their output deteriorates quickly.

3.4.3. Description of ML techniques for BD in business

In business, ML techniques have some functions that influence its efficiency. It is useful to consider these functions and their effects on ML when choosing a suitable technique. In the context of inconsistencies and inaccuracies, business databases also create noise. Inadequate data verification processes can allow incorrect data to be entered by the user. Also, during relocation from one system to another, it can become corrupt. Further, in business databases, missing data and information is another issue, particularly when data is collected from various sources, (Dutton and Conroy, 1997). Due to variations in data coding norms and aggregation strategies in various parts of the organization, all characteristics needed for analysis may not be accessible. Customer information in one unit, for instance, may include gender and level of education, while another unit may not have this information given in its database. This variation in the availability of data also occurs because of uncoordinated attempts to design databases. BD's databases may vary in size from many gigabytes to a couple of terabytes. A large range of characteristics or attributes also characterizes these BD. Therefore, the optimization of the ML technique is an essential question. A business database provides several types of data: ordinal, numeric, nominal, etc. Managing various data types by a ML technique would be more helpful for a business strategic decision, (Efstathiades, Tassou and Antoniou, 2002).

Predictive performance for a ML technique greatly affects its efficacy. First, ML systems are taught to adopt a supervised learning process. The predictive performance of the actual data system is often less than that accomplished with training data, (Saravanan, and Sujatha, 2018). An obvious desirable function is the higher predictive precision with real statistics. A company manager is mostly following the advice if the findings are explainable in business conditions. A significant element, therefore, is the ability to clarify the outcomes. As individual systems, business applications seldom run. Therefore, ease of connectivity with other IS is a valuable function of a ML's application. Before a particular technique can be used effectively, various ML techniques involve different levels of tool-related experience and awareness on the part of the end-user to make any decision. In order to prepare the data set before examination, some approaches often require comprehensive preprocessing operations. For an end-user, a technique that is straightforward to comprehend and needs fewer preprocessing operations. The behavior of ML techniques differs with variations in data and applications' operational features, (Dutton and Conroy, 1997).

4. Findings

In this chapter, the authors provide a table for the articles used in this thesis where a classification of references is presented for the major business functions that are using ML for their BD in order to help managers with their strategic decisions. It is worth mentioning that the authors include applications that were only published in authorised and peer-reviewed journals.

4.1. ML applications for BD

ML applications for BD were identified by investigating a large number of articles related to BD, ML, and strategic decisions in major business functions. Table (2) lists the applications by function area corresponding to the techniques employed that help managers with their strategic decisions. However, this is not supposed to be exhaustive. Depending on the strategic decision required, we classified such applications by their dominant classes. The major functions are Finance, Healthcare, Marketing, Government and Information Technology.

In the table below, the authors have listed decisions that are in line with the definition of strategic decisions used in this thesis: they are long-term, high risk and handle a variety of strategic opportunities and challenges facing a business. They have also been found to be major resource propositions for businesses and involve the possession of new resources and the organizing or reallocating of current resources. To make the strategic decision, the business functions use the applications listed in the table, that in turn are guided using ML and BD. For example, risk management is a long-term decision that is high risk by nature and involves both opportunities and challenges facing a business. In order to manage risks most optimally the finance function uses forecast default of loan, forecast bankruptcy, credit evaluation etc., to guide their decision. These applications are in turn guided by various methods of ML applied to BD, thus making ML and BD the basis of the strategic decision that is later taken.

Table (2): Findings Table- Source: Owen illustration

Major Area	Strategic Decisions	Applications for a strategic decision	Technique and Reference
Finance	Risk Management	Forecast Default of Loan	**RI:** Messier and Hansen (1988)
		Forecast Bankruptcy	**RI**: Sung, Chang, and Lee (1999); **NN:** Wilson and Sharda (1994)
		Credit Evaluation	**RI**: Carter and Catlett (1987)
		Approval of Loan	**RI:** Becker (1997)
		Risk Classification	**RI**: Shaw and Gentry (1990)
		Classify Financial Customer	**RI**: Rauch and Berka (1997)
		Detecting Delinquent Loans	**NN:** John and Zhao (1997)
		Recognizing Suspicious Transactions	**NN:**Brachman et al.,(1996); **RI**:Kokkinaki(1997);**RI**: Senator et al.,(1995)
	Portfolio Management	Forecast the Interest Rates	**NN & CBR:** Kim, and Noh (1997)
		Forecast the Stock Price	**NN:** Barr and Mani (1994)
		Bond Rating	**CBR & RI:** Buta (1994)
		Portfolio Management	**RI:** John, Miller and Kerber (1996)
		Forecast Price of index Futures	**NN & RI:** Tsaih, Hsu, and Lai (1998)
Healthcare	Medical Diagnosis	Hypothesis Formulation of illness	**GA:** Bhargava (1999)
		Mapping symptoms to surgical procedures	**NN & RI:** Spangler, May and Vargas (1999)
	Competitive adv. in Healthcare	AI systems to support objective decisions	**AI Systems:** Horgan, et al., (2019)
	Drugs distribution	Patient data	**DCNi, FPO, RP, ETP, SENSE, RC, Nucleus, DYNAMO:** Finelli and Narasimhan (2020)
Government	Law Enforcement	Justice System	**Mercury**: Berman, (2018)
	Traffic	Car accidents	**Random Forest, Deep Neural Network, Gradient Boosted Classifier, Gradient Boosted Classifier:** Monselise, Liang & Yang (2019)
	Communication	Science and Technology Think Tanks	**Strategic Decision Platform:** Yu & Xiao (2020)
	COVID-19 pandemic	COVID-19 Outbreak: Gupta et al., (2020)	**SEIR:** Li and Muldowney (1995)**, Regression Model:** Yang et al., (2020)
		Evaluation of Litigation	**RI:** Dale and Bench-Capon(1997); **NN & RI:** Shortland and Scarfe (2007)
	Politics	Political conflict resolution	**IDIS, CBR:** Furnkranz, Petrak and Trappl (1997)
Marketing	Entering New Market	Lifestyle Behaviour Analysis	**RI:** Lee and Ong (1996)
		Market Segmentation	**RI**: Shortland and Scarfe (1995)
	Marketing Analysis	Improvement of Cross Sales	**RI:** Anand et al., (1998)
		Support Online Sales	**CBR**: Vollrath, Wilke and Bergmann (1998)
		Customer Response to Promotions	**GA:** Bhattacharyya (1999); **RI:** Selfridge, Srivastava, and Wilson (1996)
		Analysis of Product Performance	**RI:** Anand et al., (1993); Anand (1995)
IT	Technologies	Solve Data Problems	**Four case studies:** Goel et al., (2020)
		Technology Development	**RI:** Prokhorenkov and Panfilov (2018)
		Estimation for cost of the software	**NN:** Lee and Balakrishnan (1998)
		Control for quality of the software	**CBR:** Allen (1994)
	Web Analysis	Similarity evaluation of user surfing habits	**RI**: Chen et al., (1996); **RI:** Cooley et al., (1997)
		Web pages classification based on content	**RI:** Viveros et al., (1997)
		Similarity evaluation of web page content	**ILP**: Craven et al., (1998)

4.1.1. ML applications of BD for Strategic Decisions of Finance

In finance and banking, forecasting the future is the main problem for any strategic decision. Wilson and Sharda (1994), for example, shows the importance of the NN technique for discriminant analysis in the estimation of a company's bankruptcy. 97 percent forecasting accuracy was accomplished by their NN-based technique. Another application in this field, Sung, Chang, and Lee (1999) shows that in forecasting bankruptcy under varying economic conditions, a RI-based model could accomplish higher forecasting accuracy.

Messier and Hansen (1988) suggests the use of RI to forecast loan defaulters. Their research notes that an RI-based technique can accomplish superior forecasting accuracy than discriminant analysis. The use of NNs and RI to forecast the price of the S&P 500 Index in a complex and volatile environment is also suggested by Barr and Mani (1994). By using time series data with 21 measure variables as input, the NN was trained and accomplished a forecasting accuracy of 92 percent for the shift in the change of the S&P 500 Index. Carter and Catlett (1987) define the use of the RI to evaluate the reliability and validity of an applicant for a credit card. Their research suggests that RI is an excellent technique for discriminant analysis systems within this application by using a set of data that includes both discrete- and continuous-valued attributes in order to help the top management with the process of making any strategic decision. In addition, Carter and Catlett (1987) discuss further ML techniques for derivative risk management and fixed income, and what-if analysis as a tool to support a strategic decision.

For a loan approval process and the identification of credit card fraud, Becker (1997) uses unsupervised and supervised learning. Their technique enables the development of visual decision trees for business requirements to be obtained. An Inductive learning approach is used by Shaw and Gentry (1990) for risk classification in the bond ranking process and loan assessment process. The purpose of this approach is to use a broad collection of variables to generalize the results of each process and support the related strategic decision in an uncertain environment. Moreover, it shows the superior performance of the RI technique over discriminant analysis, and Logit and Probit analysis.

Rauch and Berka (1997) describe groups of accounts from financial transaction databases, these groups described by having interesting activity patterns, such as regularly changing small debit and credit balances. Furthermore, John and Zhao (1997) discussed forecasting functions of NN for predicting delinquent loans (e.g., mortgage) from banks in an uncertain environment. The technique method, used to predict whether a mortgage is likely to become delinquent, uses features such as the loan-to-value ratio, origination amount, length and form of loan, etc. This method is one of multiple tools used to support a strategic decision. In addition, various techniques to detect suspicious transactions are used; Brachman et al. (1996) use a NN-based technique to evaluate suspicious credit-card payments and transactions; while Kokkinaki (1997) suggests using trees of similarity for a similar application; Senator et al., (1995) explains that transferring large amounts of money reflects the possibility of laundering money by using RI technique.

Likewise, in many organizations, strategic decisions for portfolio selection are a critical task and it is associated with a dynamic process involving many contexts of decision-making in a VUCA environment. Portfolio selection is a leadership skill on one side and a dilemma flipping on the other. The eventual dilemma is to take the VUCA environment of financial markets and turn it from a threatening matter, which it surely is, into an environment that is not only threatening but also carrying opportunities. This is a type of gaming in portfolio selection. ML is basically taking the not certain belief set and then examining it in various environments and testing many possible scenarios of engaging with that specific state. ML techniques, to some extent, have always expert this. That is a lot of what happens in finance when a financial manager is trying different assumptions and examining them by challenging the logic. In other words, it has existed before and not all that new. But in the VUCA environment circumstances, with being connected or interconnected and the capability of ML to imagine and create scenarios, ML have much better tools and techniques to be able to examine and try different scenarios, (Johansen and Euchner, 2013). John, Miller, and Kerber (1996) rate stocks depending on their output of return and risk and allow the individual to create stock portfolios according to his or her level of risk tolerance. More than one ML technique is used by various applications.

An integrated framework, that blends CBR with the NN technique to forecast interest rates for treasury bills and corporate bonds in an uncertain environment, was described by Kim and Noh (1997). In forecasting US interest rates, their integrated framework performed a random walk model but for forecasting Korean interest rates it was not very effective because of the higher sophistication of the former market's investors. CBR with RI is used by another hybrid framework to rate corporate bonds and was presented by Buta (1994). By complementing data gathered from principles on how to rate bonds with similarity measures acquired from previous situations of bond rating, it offers high judgment and supporting tools on more complex bond-rating situations for the strategic decision related. Their framework matched the S&P recommended scores 90.4 percent for firms with complete information; while 84.4 percent of the time for firms with incomplete information. On the other hand, Tsaih, Hsu, and Lai (1998) developed another hybrid RI-NN technique to forecast the path of the regular price fluctuations in the futures of the S&P 500 index where its environment is described by high volatility. RI subsystem picks main statistical parameters that are then used to train the next subsystem of NN, which further provides suggestions for the path of price change.

4.1.2. ML applications of BD for Strategic Decisions of Healthcare

Horgan, et al., (2019) shows the benefits of digital technologies and integrating ML into European healthcare processes and enhancing clinical services, encouraging innovative therapies and procedures, and improving the quality of medical systems. As illnesses are handled more efficiently, payers can see cost reductions linked to higher medical results, such as a decrease in the complications number. AI can achieve cost reductions of more than EUR 90 billion in the next ten years of obesity. The savings will come from a variety of ML deployments: decreased medical expenses and lowering costs from low growth and sick leave; studying the effect of intervention across various populations, attempting to extend or adjust a framework; and enhancing understanding of genetics and risk factors, metabolism, and ecological, behavioral, and food consumption factors linked to obesity, (Horgan, et al., 2019).

For creating efficiencies in Healthcare management, the growing and intensifying burden of rising worker shortages can be minimized by ML. For instance, the UK NHS has 45,000 medical vacancies and an additional 50,000 non-clinical open positions, and a similar shortage of staff can be seen in Europe. Most of these vacancies are occupied by temporary workers, which, due to the higher costs linked with temporary staff, just causes more financial pressure. ML applications, including those that perform screening before patients come to a healthcare center, would offer greater leverage for overstretched healthcare professionals, enabling them to concentrate on engaging with patients on arrival, (Horgan, et al., 2019). For new treatment opportunities, ML applications could enhance both diagnosis and treatment of breast cancer through early disclosure, treatment decisions, and decreasing the direct involvement of doctors in potential tedious activities. Enhancing diagnosis and treatment using ML applications will cut the costs up to EUR 74 billion over the following ten years, (Horgan, et al., 2019).

Finelli and Narasimhan (2020) concentrate on (operational data) and the initiatives they have taken to introduce the tech transformation into the growth of Novartis Global Drug Development and influence the way they function through strategic decisions guided by analytics. Most of what they undisclosed can translate well to "patient data" on a track scale. Examples of patient data derived from patients, hospitals, distributors, spenders, and many others are electrophysiological medical, biomarkers, laboratory, clinical trial data types, genomics, medical mapping data, proteomics and some other biological genetic data, and real-world data.

ML and advanced analytics were processed to create unique knowledge (intelligence) and to develop application techniques for associates that can provide insights on taken action (unlocking value) to schedule, monitor, forecast, evaluate and control sector activities, reduce costs while maximizing performance. This strategy allows productivity to be maximized (better, faster, cheaper) and makes wiser strategic decisions during drug growth. Based on historical data from multiple domains (BD), ML has been critical for developing techniques (e.g., patient participation), recognizing, instead of prescribing, the putative factors behind certain events with less assumptions. The ML techniques used by Finelli and Narasimhan (2020) to provide insights into strategic decisions are presented in Table (3) below:

Table (3): ML techniques provide action insights into strategic decisions - Source: Finelli and Narasimhan (2020)

Technique	Full Name	Main User	Description
DCNi	DCN insights	Global Drug Development	Offers insights into patient registration, cost and quality, and allows comparison between different research or countries.
DYNAMO	Dynamic allocation with machine optimization	Finance	Estimates the total and stage costs for every planned (scheduling) and current (monitoring) medical study.
Nucleus	Nucleus	Technical Research and Development	Enables the production of appropriate drug supply schedules and eliminates the supply risk.

FPO	Footprint optimizer	Global Development Operations	Allows selection of suitable research locations based on historical data in order to study registration scenarios.
RC	Resource cockpit	Technical Research and Development	Captures production schedule across technical divisions and facilitates optimization allocation of resources.
RP	Resource planner	Global Development Operations	For each medical study, it estimates required resources, such as personnel and time involved necessary.
SENSE	SENSE	Global Drug Development	A control tower for clinical trials, helps to track research portfolios and identify possible risks to schedules or costs.
ETP	Early trial pricer	Global Development Operations	Allows rapid estimation of clinical study costs for different scenarios and helps managers select the most relevant.

Spangler, May and Vargas (1999) also show ML is used to transform the diagnosis of patients and demographic information into surgical operations to be carried out on the patient by using both NN & RI techniques. Further, Bhargava (1999) states the use of GA technique to help with generating hypotheses concerning causes of diseases among veterans of the Gulf War. A big database includes 20,000 reports and 150 military members attributes are analyzed to classify the most significant sets of attributes among them which may be related to diseases.

4.1.3. ML applications of BD for Strategic Decisions of Government

Berman, (2018) shows the application of ML in society and throughout government in several modes for law enforcement. In the justice system, algorithmic strategic decisions are becoming central; police departments have used historical crime-related data to better allocate resources and define high crime locations or hot spots. Berman, (2018) explains Mercury as a program that seeks to enhance automated Signal Intelligence Analysis Tools (SIGINT) to predict and/or identify incidents such as terror threats, social disorder, as well as outbreaks of disease overseas.

For ML applications, the legal sector is a complex field. A few applications in this field are listed by Dale and Bench-Capon (1997), including tracking compliance with criminal sentencing guidelines, illustrating judicial decisions via defined legal principles, and extracting rules from information obtained from legal experts. Some of the challenges of building and improving ML applications in this field are managing ordinary and continuous valued characteristics, defining input parameters for continuous feature partitioning, large numbers of input variables, massive data sets which are hard to partition, and noise present in the form of outlying scenarios.

In order to predict the outcome of litigation, NNs and RI techniques were used, (Shortland and Scarfe, 2007). To analyze the effectiveness of settling a lawsuit over pursuing it, the government may use the information gathered from such techniques. Furnkranz, Petrak and Trappl (1997) discuss the use of the CBR technique to forecast the effects of international conflicts. Further, they present IntelligenceWare to determine the reliability of decisions delivered by judges and to consider judges' dominant biases.

Monselise, Liang & Yang (2019) examines several accident variables with the aim of developing a comprehensible model that forecasts the causes of accidents provided traffic conditions and speed limits and many other; as road traffic crashes continue to be among the world's causes of death. On a dataset of 7707 trips gathered by the Second Strategic Highway Research Program, the report compared four ML techniques. Random Forest, Gradient Boosted Classifier, Deep Neural Network, and Gradient Boosted Classifier with Grid Search; are the listed ML techniques. In predictive modeling for several health conditions, these techniques have been commonly used. The models were compared, for their success in precision, specificity and sensitivity.

Recently, for the entire world, the COVID-19 pandemic has now become a significant risk. Gupta et al., (2020) presents a study of this outbreak that calls for tremendous government attention in all nations to gain action in order to reduce the effects of this global pandemic. Gupta et al., (2020) analysis and forecast the outbreak of this disease based on the data obtained from the official site of the Indian government, ML techniques such as the SEIR (Li and Muldowney, 1995) and Regression model (Yang et al., 2020) were used. RMSLE was used to test the efficiency of these techniques and reached 1.52 for the SEIR model and 1.75 for the regression model. Their study found that the RMSLE error rate between both the SEIR technique and the Regression model was 2.01. R0 value, which is the distribution of the virus, was also estimated to be 2.84. In the three-week duration of test results, which is very similar to the actual figures, expected cases are estimated at around 175K-200K. Gupta et al., (2020) research assists the government and practitioners in planning their future.

The Yu & Xiao (2020) study supports the open research of experts in science and technical think tanks and the academic strategic decision of governments to respond to the scope and BD attributes of scientific and activities of technological innovation in the contemporary world. The data, information, application, decision and feedback model of the five-layer architecture decision platform.

Their platform fulfills different criteria such as intense analysis of the think tank experts, transparency for the process of strategic decisions, and innovator participation, especially innovative which construct a closed-loop workflow of the forward strategic decisions and backward feedback processes, which allows different think tank, decision-makers, experts, and innovators in technology to engage in this platform. Shape a collective decision-making group and meet the aims of enhancing the scientific and productive strategic decision of technical and scientific innovation, (Yu & Xiao, 2020). The diagram of the platform for strategic decisions is presented in Figure (4).

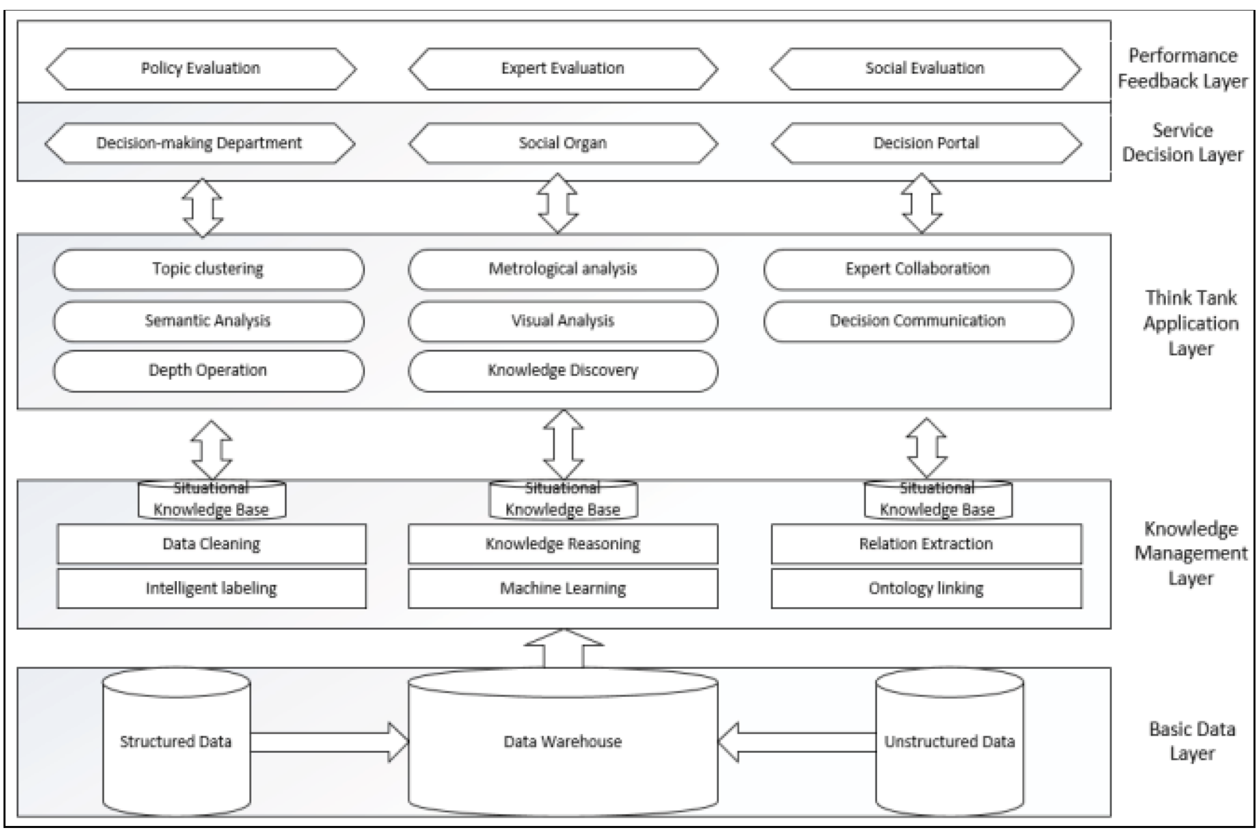

Figure (4): Diagram of Platform for Strategic Decisions - Source: Yu & Xiao (2020)

4.1.4. ML applications of BD for Strategic Decisions of Marketing

By examining online marketing, the correlation between demand and price in the real estate sector has been explored (Pangallo, and Loberto, 2018). ML is used to distinguish pairs of duplicate ads that belong to the same house unit. Further, by using a knowledge-base and promoting the 24/7 accessibility of customer service centers, an ML technique has been developed to provide highly precise automated responses and a successful tool for a strategic decision (Kurachi, Narukawa, and Hara, 2018). The ML technique improves the effectiveness of the supporting services and automates the processes of digital environment. Furthermore, to forecast the degree of visibility of corporate websites, ML techniques were developed (Pant and Pant, 2018). Using ML techniques, a trend hashtag generates applications for social media business users to achieve a wide reach of the targeted audience (Abeywardana et al., 2018). Another technique was implemented by Mackey et al., (2018) using ML to efficiently identify the marketing and selling of opioids via illicit online sellers through Twitter.

For strategic decisions related to entering new markets; Market Basket Analysis, Analysis of Retail Sales, Market Segmentation Analysis, and Product Performance Analysis are some ML applications for strategic decisions in marketing. In order to differentiate between users and non-users of telecommunications goods, British Telecom uses RI (Shortland and Scarfe, 2007). This data allows the tailoring of innovative services to closely suit the needs of customers. Cross-sales — for example, the sale to existing customers of a product with advanced functionality, can be increased by aligning customer attributes towards product features. Lee and Ong (1996) has been used in many households in Singapore in order to examine transportation, food, shopping, and travel habits. They used RI technique to evaluate customer product performance and to define factors affecting this performance. This technique helps the management within the process of strategic decision by comparing the performance of multiple stores with the benchmark interactively. They discovered that supermarket products such as dry-food condiments and bread are commonly sold together. They further observed a close connection in hardware stores between customers that are buying discounted hardware goods and plumbing products.

Anand et al. (1998) define a technique focused on RI to classify potential customers for a new insurance product provided by a bank from the customer accounts of that bank. Furthermore, Selfridge, Srivastava, and Wilson (1996) examine the effect of new marketing campaigns on customer behavior in the telecommunication industry. It offers customer features with interactive questions and drill-down functionality. The use of GA to identify clients who are most likely to react to a marketing strategy is discussed in Bhattacharyya (1999). This paper investigates the mailing depth needed to maximize the profit on advertising under a set budget (i.e., the proportion of clients to whom the marketing campaign needs to be targeted). GA was used in connection with other ML techniques in marketing applications.

Anand et al. (1993) is an ML approach based on explanations that are used for strategic decisions related to the analysis of product performance. Due to the implementation of new marketing campaigns and shifts between product categories, this may imply changes in the market share of a product. A sales manager may also use Opportunity-Explorer by Anand (1995), a later version of Anand et al., (1993), to evaluate his/her market with individual stores. Vollrath, Wilke and Bergmann (1998) is able to process vast amounts of marketing data to provide managers with significant information on emerging opportunities, risks and deviations from patterns. CBR has been used for strategic decisions related to sales in a novel application involving shopping online. This technique estimates the measure of similarity between the product requested by the customer and the product provided by the company and provides the customer with a case-based list of items with identical features.

4.1.5. ML applications of BD for Strategic Decisions of IT

Goel et al., (2020) explores some prospects of using BD analytics combined with cloud services in order to deliver solutions to boost industrial processes. Their article identifies the plan and a systemic structure that illustrates the lifecycle of data analytics in the field of industrial processes, quality control and protection of the environment. Four case studies are used: (1) barrier assessment for dynamic risk mapping (DRA), (2) Natural Language Processing (NLP) for mining text, (3) Deep-learning based predictive maintenance monitoring modeling, and (4) correlation development for sustainability indicators. It also addresses the problems of both analysis and the implementation of the solutions proposed in industrial processes. It is suggested that a well-balanced structured technique is needed to allow more accurate strategy, which facilitates strategic- and risk-based decisions, leading to safer, effective and more innovative products. This includes ML-supported decisions combined with professional expertise and accessible data from diverse key resources, (Goel et al., 2020).

Prokhorenkov and Panfilov (2018) suggests that the challenges of recognizing and predicting patterns, as well as the demand for advanced technologies, can be tackled by the aid of widely obtainable BD technology, ML, and predictive analytics. As companies today show great consideration to the IP portfolio, which is a crucial competitive advantage and strategic edge, this makes patent applications one of the essential strategic elements of a company plan, as well as the evaluation and identification of potential trends. Patent analytics defines the method of evaluating vast volumes of intellectual property data to reveal relationships and patterns. Therefore, Prokhorenkov and Panfilov (2018) has an efficient development and advancement strategy. Prokhorenkov and Panfilov (2018) focuses on clustering techniques, the processing of massive text files and patent database search engines. A workable strategy for bringing patent data into the BD analysis space is the proposed solution described here. Perspectives from BD analytics applications are expected to have a significant effect on strategic decisions, eventually giving chief IP officers chances to take on more strategic decisions within their corporations.

Allen (1994) employs CBR to spread understanding for quality of a software to help with strategic decisions among managers, professionals, and software engineers. To allow easy sharing of this information, experts report on software quality issues and their responses are gathered in a case base. Furthermore, Lee and Balakrishnan (1998) address a hybrid system to the calculation of software costs. To group related projects, cluster analysis is used. A project cluster's characteristics are then used to identify the suitable NN technique for cost analysis. The characteristics of this software are used to measure the project cost as a reference to this NN.

In addition, ML applications in web analysis are used with the growing popularity of electronic commerce, the World Wide Web (WWW) has attracted the attention of ML researchers such as discovering usage patterns for strategic decisions in the WWW (Etzioni, 1996). To identify access patterns of WWW users, ML has been used to examine log file data (Chen et al., 1996). This data is useful for optimizing access to websites. Cooley et al., (1997) also uses RI to find grouping rules, clusters, association rules, sequential access trends from site access data using a SQL-like query process. Viveros et al. (1997) examines data on web usability to produce path-based, group-based, and user-based description reports on the length of user session, range of websites visited via users, and paths and pages most frequently visited. In Viveros et al., (1997), several ML algorithms including association rules, clustering, and sequential patterns are used to categorize HTML pages and to discover correlations between WWW users' interests. The aim is to provide recommendations on which cluster of pages to view by new users, relying on their preference of interests.

A variety of ML applications concentrate on material from the internet. Craven et al., (1998) quarries information included in the links connected indirectly to WWW documents. This can be used when looking for Web pages if the positions of the desired websites are not specified. Instances of such apps include finding the homepages of users, new locations of transferred pages, as well as any uncategorized content. In a related manner, Viveros et al. (1997)'s CLEVER framework explores the WWW for authorities (sites that provide the best answers to the research questions) and hubs (sites that collect references to authorities) and produces more related pages than other search engines. For learning descriptions of page categories and relations between sites, a classification-based ML technique is used in Craven et al., (1998) by using the information of relation between different site groups, this method enhances strategic decisions related search accuracy and time.

5. Discussion

In this chapter, the authors provide a comprehensive discussion for the articles presented in the previous chapter "Findings" where we discuss the roles of Machine Learning and Big Data in order to help different organizations with their strategic decisions. The discussion is presented in the same order of the classification presented in the Table (2).

In Finance, strategic decisions are extremely important as the competition and technological rate are so high, and market information is obsolete or unavailable most of the time. Further, financial strategic windows are opening and closing rapidly, which will lead to a high cost of error. Mathematical analysis of modern advancements, advanced software and hardware, and the quality of being able to use BD has provided the machines with the possibility to run as financial analysts, investment managers, and traders. Moreover, in a VUCA environment strategic decisions are problematic, as mentioned above in accordance with Sattar (2016) and described with a high rate of change such as finance, for example, not just because the change is very dramatic but also because it is hard to forecast the impact of the change as it is happening.

As an outcome, it is very straightforward to make a poor strategic decision. In this setting, however, the strategic decisions of "wait and see" and "me too" can also lead to failure for most organizations and especially in Finance where the competitive advantage positions change and the opportunity windows close. Further, in this setting, the challenge of strategic decisions is that it is simple to make a mistake by moving too fast, yet equally inefficient to postpone a strategic decision or duplicate others. As a conclusion, one of the most prevalent applications of ML in finance is process automation. ML allows human work to be replaced, and productivity to be improved. The process of gathering more precise data and information at the micro-level by ML will help financial managers in approximate risks with the capacity to boost profits, and eventually, with their strategic decisions through accomplishing superior forecasting accuracy in a VUCA environment, scale up services of risk classification, predicting delinquent loans, forecasting interest rates, and portfolio selection.

Healthcare sector is one of the main winners from the implementation of ML in their strategic decisions in a VUCA environment. Instead of being an idea, accuracy and personalized healthcare become reality, patient outcomes can be improved significantly, medical professionals will gain new control and power, and efficiencies can be increased in the healthcare industry. Personalizing and accuracy care means more productive and effective care, minimized waste of time and money, increased patient satisfaction, due to the fact that the deployment of AI results in huge cost-savings. Essentially, the pharmaceutical industry and healthcare are data driven. Healthcare professionals such as doctors wrap molecules around in those data along the whole value chain from science to market: to highlight their mechanisms of action, their protection, and effectiveness, and finally to advise medical professionals how to efficiently use them to boost or improve patients' lives while treating them. Unlike typical rule-based software, which requires detailed instructions to complete a mission, ML offers a technology power not only of accelerated and super-human analysis, but also of taking actions appropriately to accomplish or support a strategic decision. In order to define and analyze complex and non-linear relationships across large datasets of BD in healthcare, a robust mathematical technique, at the heart of ML, uses several algorithms for this purpose.

As a conclusion, the healthcare industry is a VUCA sector, and one of the most successful in terms of mergers and acquisitions among the largest sectors. Furthermore, it has become one of the most heavily regulated sectors recently, with more strict standards and government regulations changes. In fact, the industry is experiencing dramatic changes as (1) medicine gets more personalized, (2) health data becomes highly valuable, and (3) data sharing is made obligatory. The value of ML in healthcare is the ability to control and process big and complex volume of data that are beyond the human comprehension capability, then efficiently turn interpretation of these data into valuable insights in order to help healthcare's professionals with their strategic decisions, and, eventually, leading to better results, create unique knowledge, lower healthcare costs, and improved patients' lives.

For governments, the importance of strategic decisions is coming from pursuing new strategies for governments' service portfolios through integrating both the private markets of for-profit companies and intergovernmental negotiations for public markets, and through building transparency by accessibility of relevant data. Strategic decisions affect government strategies, legislation, and actions. The shortage of effective ML and computational algorithms used in public sectors contributes to 1) the strategic decision process is slower than other types of decisions; 2) the 'entire picture' of public sectors is not clear along with all data required, especially in a VUCA environment; and 3) little effect is generated by strategic decisions, among others.

Strategic level planning and strategic decisions developed by government parties who carry political and administrative responsibility offer public accounts of events, enforce and encourage strategic-planning, -cooperation, and -collaboration required. Hence, ML techniques can help government parties effectively in their strategic decisions in a VUCA environment. It is expected that the government's strategic decision aims to use the predictive capacity of ML for the public sector in this VUCA environment. In the sense of law enforcement and national security, these techniques have also made major inroads. Forecasting using ML techniques, in law enforcement and national security, promise to provide a better distribution of government resources, decrease the level of strategic decisions bias, recognize illegal activity that would otherwise go unreported and provide useful information about those who bring harm to the societies' national security. As a conclusion, Federal agencies are particularly vulnerable to VUCA due to persistent budget uncertainty, regular leadership changes, numerous parties with conflicting interests, and complexity that slows down initiative. However, organizations that succeed despite it all adopt VUCA and see it as an outlet for serious reform. ML algorithms, when used wisely, can enhance government strategic decisions by increasing precision, reducing human bias, and improving overall managerial performance. The public sector will legitimately explore opportunities to profit from the same kinds of benefits that ML algorithms are offering the private sector.

In Marketing, analyzing the successful execution of marketing campaigns often represents part of the strategic decisions for different organizations. This stage is overlooked or entirely ignored by many organizations, which can cause disturbance in future strategic decisions. The analysis of the strategic plan adopted helps to strengthen the decision-making process and recognize shortcomings at all levels of strategic planning. BD and ML should be used in today's technology which is described by VUCA in order to optimize the strategic decision, improve the probability of success, result-oriented strategy execution and boost the organization efficiency. ML can be viewed in marketing as shallow data analysis, concerned only with one layer of information acquired (Polson and Sokolov, 2017). ML simultaneously manages a huge amount of marketing data in order to provide different solutions for a strategic purpose. The use of ML in marketing can expose the complex relationships among all marketing variables in BD such as sales, promotions and product performance. Thus, ML leads to a more successful strategic decision and operates on the premise that different types of data are fed to the machine, then that data is analyzed, the system, at the end, takes these variables into account for the strategic decision process.

Marketing is highly sensitive in a VUCA environment. Recently, the way of supporting, promoting and engaging with clients has fundamentally changed. In the meantime, the rate of shift in culture, customers and technology, is increasing and evolving at a fast pace. The rapid advancement of technology impacts shaping and brands for related strategic decisions of marketing agenda, as customer preferences rise towards more customized, meaningful, and assistive interactions, ML is becoming an essential application to help fulfill those requirements. It allows the advertisers to create smarter segmentations of customers, understand the competitor, produce more innovative campaigns and strengthen the market positioning. Moreover, it allows the advertisers to align the products with changes in customer needs, look after the existing customer, predict the future and plan the strategy to remain competitive in the environment of VUCA, and measure and monitor performance more accurately.

Finally, Technologies such as the Internet of Things (IoT), Virtual Reality (VR)/Augmented Reality (AR) and Artificial Intelligence (AI) have become critical for enhancing productivity for most organizations. Further, such technologies drive the performance of different assets owned by organizations, support their strategic decisions, protect various processes involved, and manage any abnormal situations that might occur. The dynamics of ML and its implementation for different core structures make it easier to adopt new applications for strategic decisions with real-time data and advanced computing techniques. In industrial processes, evolving sensors, network technology, connected platforms and computers will potentially result in an immeasurable set of data. This allows the potential to innovatively solve problems. Since much of the data tends to be semi-structured or unstructured, new techniques can be designed and implemented by organizations in order to help with the process of strategic decisions in a VUCA environment. In addition, workflow architectures with data analytics are required before prototype strategies can be created, including ML techniques.

In a VUCA world, organizations are struggling to keep up with the acceleration in IT and the complexities of foreign markets in almost every industry. Because of technologies beyond microprocessor control, such as cloud computing, touch screen technology, social media, broadband, and a very large quantity of personal computers in society, innovation in IT happens even quicker than it did before. Due to this, there is important, and instant, access to even more data to make a strategic decision in the VUCA environment. ML can be beneficial in IT by recognizing and predicting patterns, the demand for advanced technologies, accessible data from diverse key resources, provide recommendations on which cluster of pages to view by new users, rely on their preference of users' interests, and enhance strategic decisions related to search accuracy and time.

6. Conclusion

In our research, we have examined the use of BD and ML for strategic decisions as a response to the dynamic environment the VUCA world creates for organizations. As it is yet in an emerging state, the material found is rather limited, however, we do see its promises when it comes to making strategic decisions. As stated before, in order to counteract the negative effects that the VUCA world brings to the table, organizations need to develop agility. One way to create and foster the agility needed is that of implementing fast decision-making practices in the business, so that the senior executives in charge of the strategic decision do not spend too much time deciding on how to react to one change in the environment, while other changes happen simultaneously. Bearing this in mind, we conclude that the incorporation of BD and ML in organizations' strategic decisions most definitely speeds up the decision-making process, and thus leads them to be more agile. As mentioned, ML applications can analyze an immense amount of complex data at a rate the human mind can't achieve. Therefore, we argue that BD and ML is an answer to making strategic decisions in a VUCA environment. Regarding the first research question, namely "*What are the roles of Machine Learning and Big Data in strategic decisions?",* we conclude, based on our meta-analysis, BD and ML's roles are to lead the organization to enhance its predictability, decrease costs, lower human bias, and improve top management performance.

Based on the meta analysis of the articles and to answer the second research question, namely "*How do organizations apply BD and ML in their strategic decisions?".* In finance, ML helps financial managers with their strategic decisions by accomplishing superior forecasting accuracy in a VUCA environment, scale up services of risk classification, predicting delinquent loans, forecasting interest rates, and portfolio selection. Further, in healthcare, the value of ML is its ability to analyze big and complex volumes of data beyond the human comprehension capability, and then efficiently turn the interpretation of that data into valuable clinical insights that help healthcare's professionals in strategic decisions, eventually leading to better results, create unique knowledge, lower healthcare costs, and improved patients' lives. Moreover, ML algorithms, when used wisely, can enhance government strategic decisions by increasing precision, reducing human bias, and improving overall managerial and leadership performance. The public sector will legitimately explore opportunities to profit from the same kinds of benefits that ML algorithms are offering the private sector. In addition, ML is becoming an essential application to help fulfill marketing's requirements. It allows the advertisers to create smarter segmentations of customers, understand the competitor, produce more innovative campaigns, strengthen the market positioning, align the products with changing customer needs, look after the existing customer, predicting the future and plan the strategy to remain competitive in the environment of VUCA, and measure and monitor performance more accurately. Furthermore, ML can be beneficial in IT by recognizing and predicting patterns, the demand for advanced technologies, accessible data from diverse key resources, provide recommendations on which cluster of pages to view by new users, rely on their preference of users' interests, and enhance strategic decisions related search accuracy and time.

Big Data is modern and requires investigation and comprehension of both technological and market criteria. Indeed, BD is not a stand-alone system, but rather a synthesis of technological advances over the last 50 years. Big Data's great benefit is the potential to consolidate vast volumes of data without all the complicated programming required in the old days. Big data, on the other hand, has shown great potential for strategic decisions, as well as for promoting connectivity between governments, individuals and industries, and for bringing in a new age of digital infrastructure.

ML and its application are now becoming more important and beneficial in most major business functions. ML benefits can be seen in the form of enhanced product marketing, help with reliable revenue predictions, rapid analysis processing, explain the meaning of previous customer behaviors, facilitate correct diagnosis and medical forecasts, simplify and shortcut the time-intensive for documentation in data entry, improve the accuracy of financial guidelines and frameworks, fast identification of spam, stronger segmentation of customers and recommending the correct product. All these features made ML a key trend for technical creativity and generates a higher value. In addition, ML helps organizations to uncover new themes and patterns from broad and complex data sets smoothly and continuously. Three specific features of "disadvantages" for ML are related here. First, in terms of intelligibility for humans, many computational methods arising from the ML process cannot be interpreted. Therefore, it requires time and effort to learn to understand different methods of ML. Second, ML and its expectations are focused on established associations within a data set instead of the confirmed causal relationships. The consequence is that inevitable mistakes would be random in every way, even though they are considered low. Third and finally, models created by ML eventually represent their programmers' beliefs, biases, and opinion calls, mostly in aspects that are unseen on the surface of the algorithm. Hence, in some sense, ML is still dependent on the decision-maker's personality. In order to make strategic decisions in a VUCA environment using BD and ML, top management should also optimize their analysis to improve experiences. This encourages businesses to offer new goods and services that are customized or differentiated. It may, however, be a profitable choice to recognize ML as a strategic initiative. Still, it could bring some risks e.g., data poisoning attacks. It is smarter, therefore, to treat strategic decisions with the utmost consideration.

6.1. Suggestions for further research

As the use of ML and BD for strategic decisions is still rather new, further research in its appliance should be carried out. However, to increase the significance of the study, one should focus on a certain business environment or industry, for the conclusions to be generalizable. As we decided to analyze the general use of ML and BD in strategic decisions and thus incorporate several major business functions that use it, the conclusions we are able to draw are rather limited and thus cannot be generalized. An interesting take on furthering the research would be to compare the use of ML and BD for strategic decisions to that of rational/limited rational strategic decisions and intuitive strategic decisions. As we had a limited amount of time to conduct our research, this was not an option for us, and therefore we cannot say that ML and BD is better suited than the other methods when it comes to strategic decisions. Thus, comparing them and highlighting data on which performs best, especially in a VUCA context, could help executives know which method to use and therefore increase the significance of the study. Furthermore, as we have seen during the research, there are multiple methods of ML, each having their pros and cons and thus suited differently for various contexts. Therefore, we conclude that further research could delve deeper into the different methods and compare each methods' appliance on strategic decisions in order to see which kind of method is best for the specific strategic decision at hand.

7. References

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