University of Oran 2

Faculty of Economics, Business and Management

Dissertation submitted in partial fulfillment of the requirement for the degree of PhD in management sciences

Option: Entrepreneurship and SME Management

DECISION MAKING BASED ON DATA ANALYSIS IN BUSINESS

Presented publicly by: BOUAOULA Wassila

Jury Members

Pr	BENBAYER Habib	University of Oran 2	President
Pr	BELGOUM Farid	University of Oran 2	Supervisor
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Dr	BRAHAMI Mohamed Amine	Université de Formation continue	Examiner
Dr	KATEB Karim	Oran Graduate School of Economics	Examiner

Academic Year 2021-2022

Dedicated to

My husband and parents

My son

My brother and sister

My late grandfather who barely

could read and write but taught

me how education is important

for a woman

All my loved ones

Acknowledgements

I would like to express my sincere and profound gratitude to my supervisor Dr. Farid Belgoum for his guidance and untiring support throughout my doctorate research at *University of Oran 2.* I must assert that I have benefitted immensely from his versed expertise in the field of my research. His advice and resourceful suggestions have made my program a fruitful one. I am thankful to other professors and researchers, for their critical comments and constructive remarks in improving the quality of my research papers.

I am highly grateful to my parents, sister, brother and my husband Mohammed, for being there for me through thick and thin.

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Abbreviations

AHP	Analytical Hierarchy Process
BI	Business Intelligence
DDDM	Data Driven Decision Making
HiPPO	Highest Paid Person’s Opinion
IT	Information Technology
SAHP	Simplified Analytical Hierarchy Process
OODA	Observe-Orient-Decide-Act loop

General Introduction

Not quite long ago, data has gained importance to enhance decision-making in organizations. However, big data due to its characteristics like variety, fast changes and high volume, can no longer be effectively analyzed with traditional data analysis techniques to generate values for knowledge development. Hence, new models and methodologies are required to analyze this big data through advanced data analytics and create real-time knowledge for effective decision-making by organizations

Data-driven decisions are better decisions. Using big data allows managers to decide on the basis of evidence rather than intuition. For that reason, it has the potential to revolutionize management (Mcafee & Brynjolfsson, 2012)

Organizations are investing in data analytics to gain a competitive advantage, The growth in the quantity and diversity of data has led to data sets larger than is manageable by the conventional, hands on management tools (Neal, 2012) (Waller & Fawcett, 2013). New technologies will allow data scientists to passively collect, store, and analyze much more data in real time (Naimi & Westreich, 2014). According to (John Walker, 2014) data has to be accessible to the different levels in the organization to influence the decision, data allows us to make decisions instead of following intuition. Whether a larger but messier data set is preferable to a smaller but less messy data set is a substantive question (Naimi & Westreich, 2014). Technology facilitates greater transparency and visibility throughout enterprise ecosystems. Real-time situational awareness dramatically increases. But the managerial and operational ability to act on that data-driven information may not (Schrage, 2016) As organizational decisions increasingly become more data-driven, top managers need to assure the right decisions are data-driven as well. That explains why so many organizations have made data governance a strategic and organizational priority. Instead of more traditional IT governance, which seeks to create greater accountability for IT systems management, data governance recognizes that data is the mission-critical asset to manage (Schrage, 2016) Technology facilitates greater transparency and visibility throughout enterprise ecosystems. Real-time situational awareness dramatically increases. But the managerial and operational ability to act on that data-driven information may not (Schrage, 2016).

The concept of a decision-making process can be found in the early history of thinking. Decisions should be the result of rational and deliberate reasoning.

Plato argues that human knowledge can be derived based on reason alone using deduction and self-evident propositions. Aristotle formalized logic with logical proofs where someone could reasonably determine if a conclusion was true or false(Buchanan, 2006)

However, not all decisions are perfectly rational. Often, we let our system thinking–intuition–make decisions for us. Our intuition is based on long-term memory that has been primarily acquired over the years through learning and allows our mind to process and judge without conscious awareness.

Decision-making is considered relatively new in terms of business applications. It was mostly used in administration. Scholars such as Herbert Simon, and Henry Mintzberg—founded the study of managerial decision making."

The study of decision-making is a set of intellectual disciplines: mathematics, sociology, psychology, economics, and political science (Smirnova & Yuldashev, 2019). In fact, over the years we have regularly been coming to terms with constraints: Complex circumstances, limited time, and inadequate mental computational power reduce decision makers to a state of "bounded rationality," explains Simon. While Simon suggests that people would make economically rational decisions if only they could gather enough information. Antonio Damasio demonstrates that in the absence of emotion it is impossible to make any decisions at all (Antoine et al. 1997).

Theorists explored methods to obtain at least acceptable outcomes and not necessarily perfect ones. despite the imperfection of the decision-making process. Risk is an inescapable part of every decision. For most of the everyday choices people make, the risks are small. But on a corporate scale, the implications (both upside and downside) can be enormous. Even the tritely expressed (and rarely encountered) win-win situation entails opportunity costs in the form of paths not taken (Reyna & Rivers, 2008)

To conduct a proper decision analysis, leaders must carefully quantify costs and benefits, their tolerance for accepting risk, and the extent of uncertainty associated with different potential outcomes. These assumptions are inherently subjective, but the process of quantification is nonetheless extremely valuable. It forces participants to express their assumptions and beliefs, thereby making them transparent and subject to challenge and improvement. To make good choices, companies must be able to calculate and manage the attendant risks (Yulianto & Kasahara, 2018)

Today, sophisticated tools can help them do so. But it was only a few hundred years ago that the risk management tool kit consisted of faith, hope, and guesswork. That’s because risk is a numbers game, and before the seventeenth century, humankind’s understanding of numbers wasn’t up to the task.

While some decisions are simple, a manager’s decisions are often complex ones that involve a range of options and uncertain outcomes. When deciding among various options and uncertain outcomes, decision makers need to gather information, which leads them to another necessary decision: how much information is needed to make a good decision? Decision makers frequently make decisions without complete information; indeed, one of the hallmarks of an effective leader is the ability to determine when to hold off on a decision and gather more information, and when to make a decision with the information at hand. Waiting too long to make a decision can be as harmful for the organization as reaching a decision too quickly. Failing to react quickly enough can lead to missed opportunities yet acting too quickly can lead to organizational resources being poorly allocated to projects with no chance of success. Effective decision makers must decide when they have gathered enough information and must be prepared to change course if additional information becomes available that makes it clear that the original decision was a poor one. For individuals with fragile egos, changing course can be challenging because admitting to a mistake can be harder than forging ahead with a bad plan. Effective managers recognize that given the complexity of many tasks, some failures are inevitable. They also realize that it’s better to minimize a bad decision’s impact on the organization and its stakeholders by recognizing it quickly and correcting it (Mukerji, 2013)

In the empirical part, we used the descriptive-analysis method of research. We aimed to describe the decision-making process by further analyzing it, which in this case involves creating two new methods that help the decision-makers to make their decision. The first one is to help the decision maker measure the impact of the implementation of BI on the competitiveness of his company while the second one helps the decision-maker to classify qualitative factors according to their importance.

The problematic: how to effectively involve the data in decision-making?

Hypotheses:

H1: there is an impact of data analysis on decision-making.

H2: quantification of the qualitative data improves decisions.

Discussion Questions:

1. What challenges does the decision-maker face in the process of making data driven decisions?
2. How can a decision maker consider qualitative data in his decisions?
3. What are the advantages of data driven decision making?

In order to answer the problematic, we will discuss in Chapter 1 a comprehensive summary and the conceptual frame of big data, Business Intelligence. Chapter2 presents Data visualisation techniques and big data tools. Chapter 3 is devoted to Decision-making in organizations with a focus of decision-making in 21st century. We assigned Chapter 4 to the impact of business intelligence through knowledge management. Chapter 5 is dedicated to Simplified Analytic Hierarchy Process (SAHP) for Business Decision Making.

CHAPTER 1

CONCEPTUAL FRAME OF BIG DATA AND BUSINESS INTELLIGENCE

Introduction

Everyday, we create over 2.5 quintillion bytes of data, which is so big that 90 % of the data in the world today have been created in the last two years alone (IBM, 2017). Data is growing. e-health and wearable technology, for instance. There is a huge volume of data which is collected in the form of sensor data, weather data, video surveillance data, road traffic data, e-health, earthquake data, oil and natural gas data, atmospheric data and many more (Patgiri & Ahmed, 2017) As such, big data is working in the background and enables organizations to analyse an unprecedented amount of information(Björkman et al., 2017). Big data is created at a high speed and from variety of sources. It's part of the daily live. Organizations are having an unusual amount of data to treat.

The importance of data in decision lies in consistency and continual growth. It enables companies to create new business opportunities, generate more revenue, predict future trends, optimize current operational efforts, and produce actionable insights... Data driven business decisions make or break companies.

Section 1. Big Data

1.1 Definition:

(Baro et al., 2015) defined big data based on their literature review as "Big Data is a term used to describe information assemblages that make conventional data, or database, processing problematic due to any combination of their size (volume), frequency of update (velocity), or diversity (variety)". Veracity is a fourth "V" sometimes added to describe big data challenge. Some authors mention a fifth "V": valorization.

The definitions of the Vs that describe the big data according to (RAMESH SHARDA, DURSUN DELEN, 2014) are as follow:

1.1.1 Volume: is the common characteristic of Big Data due to the advanced technologies allowing the massive collection and storage of the data.

1.1.2 Variety: some many types of data are being generated from traditional databases, hierarchical data stores, text documents, e-mail, XML, meter-collected, sensor-captured data, video, audio.

1.1.3 Velocity: how fast data is being generated and how fast data must be processed.

1.1.4 Veracity: used by IBM to describe how trustworthy is Big Data

1.1.5 Variability: big Data can have periodic peaks, making it hard to manage in particularly with social media.

1.1.6 Value proposition: big data allows organizations to detect patterns more than small data and gain greater business value

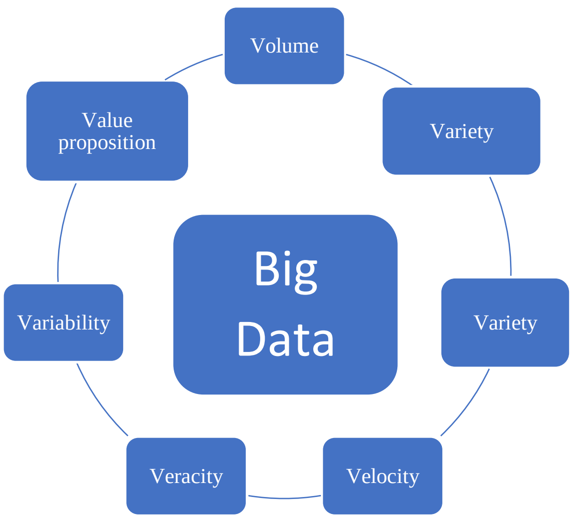


Figure 1. Characteristics of Big Data by author

According to the same author (RAMESH SHARDA, DURSUN DELEN, 2014) around 85% of the data is unstructured or semi structured and hence must be included in the analyses to support decision making.

It is when organizations use data in their decision-making that they are becoming data-driven

Data is the raw information, once treated and put into a context it becomes useful information. If that information is processed and used it becomes knowledge. The way how data is exposed to end-user is extremely important, some tools are too complex to understand and use. The maximum benefit is drawn when the knowledge produced from the Big Data analysis is used for decision-making. the right knowledge, to the right people, at the right time (Chen et al., 2008).

Data is available, the challenge now is the display and the share of information. In purpose of the organization to become data-driven decision-making promoting a knowledge-sharing policy is necessary (Stewart, 2012).

1.2 Data driven decision-making

If big data analytics is disseminated efficiently to end-users it will likely have some kind of impact on their decision-making(RAMESH SHARDA, DURSUN DELEN, 2014). Whether they act upon the insights or not and what implications it has on their work is arguably situational. Captain Edward Smith of the Titanic was known to be both competent and smart, yet he ignored warnings of an approaching iceberg and went onward, causing one of the most well-known disasters in history(Boykins, A. D., & Gilmore, 2012). There are countless of examples where presumably smart people making bad decisions. Why is this so common one may ask?

Simon(Simon, 1957) is famous for introducing the theory of bounded rationality. In order to make the best decisions, people should follow a rational process every time they make a decision. However, in reality, it is very rare case, as people are affected by factors such as time constraint, information overload, laziness etc. Simon argues that human judgment is therefore bounded in its rationality and that we can better understand decision-making if we study actual decisions rather than prescriptive decisions. Stanovich and West (Kokis, J. V., Macpherson, R., Toplak, M. E., West, R. F., & Stanovich, 2002) divides human decision-making into System 1 and System 2 thinking. System 1 thinking is based on intuition, which is decisions made fast, automatic, effortless, implicit, and emotional. System 2 thinking, on the other hand, is more rational and is characterised by consciousness, effort, explicitly, and logic. Most of our decisions are made with System 1 thinking even though System 2 thinking in many cases would lead to better decisions. The System 1 type of decisions is not only made by humans in their everyday life, but also in their professional setting. Organizational decision-making has traditionally been guided by the expertise and the intuition of those who are perceived as experts (Caputo, 2013).

An expertise based intuitive decision-making process is heavily reliant on that the decision-makers are very well aware of their own capabilities, and just like Captain Edward Smith with the Titanic, this may prove to be a risk for organizational well-being. In more recent literature (Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, 2015).

Captain Smith would be described as a HiPPO (Highest Paid Person's Opinion). A HiPPO is the antithesis of data-drivenness, who overrides what the data says if it is not corresponding with his/her own intuition. Even though expertise and intuition is valuable, it is argued to lead to less informed decisions than decisions based on data (Moya-Gómez, B., García-Palomares, J. C., & Gutiérrez, J. Salas-Olmedo, 2018).

Hence, the HiPPOs in organizations can be just as deadly as an iceberg for businesses, as it does not matter how good analyses you conduct if it is just going to end up as an unread report by a decision-maker whose mind has already been made up (RAMESH SHARDA, DURSUN DELEN, 2014).

Human bias indeed seems to be a problem within decision-making with the emergence of computer technology and more recently big data, organizations can shift from System 1 thinking to System 2 thinking, hence make better decisions (Caputo, 2013). (Waller, M. A., & Fawcett, 2013)argue that big data offer organizations an unparalleled opportunity to extract information that can lead to increased business results. Ideally, data-driven decision-making results in more agile organizations where decisions are made lower down in the organization, will lead to faster decision-making, and more empowered employees (Ruch, S., Züst, M. A., & Henke, 2016). If this is achieved, the decision-making can be argued to move from the elite few (HiPPOs) to the empowered many (IBM, 2017).

1.3 Implementing Big data in organizations

The ability to make sense of unstructured data through analytics enables organizations to incorporate valuable insights about their business into their everyday routines, processes and decisions. This likely means that organizations need to gather data, analyse it, turn it into insights, and then make sure that the insights are acted upon(Waller, M. A., & Fawcett, 2013). If this is done efficiently, organizations can gain competitive advantages from being well-informed about their business and possibly increase their performance(Marr, 2015).Hence, big data basically gives organizations an opportunity to be more competitive. However, these opportunities do not come without challenges, big data is not just a technology initiative. It is a business process that requires technology. In order for big data to achieve its full potential, it must be incorporated into organizations strategy and decision-making. Thus, in order for organizations to capture the true value of big data, they must re-define their processes and way of doing things (Hallegatte, S., Shah, A., Brown, C., Lempert, R., & Gill, 2012). Because of the amount of data being generated and the knowledge gained from that data, (El Houari, M., Rhanoui, M., & El Asri, 2015) argue that big data is fundamentally a new way to gain knowledge in organizations. Being able to utilize the knowledge gained through big data analytics will enable organizations to make faster and better decisions, and the biggest obstacle they will be facing is to incorporate the data-driven insights into their day-to-day business processes (Ray, P. K., Mohanty, S. R., Kishor, N., & Catalão, 2013).

1.4 Data as a competitive advantage

The competitive advantages of data science have been explored in existing literature. Organizations are constantly trying to win new customers without losing their hold on their existing customers (Helmreich, 2000). Those organizations that know how to leverage the competitive advantages of data science have been able to distinguish themselves from the rest of the pack (Jibril, T. A., & Abdullah, 2013). According to the McKinsey Global Institute (MGI), data-driven organizations are now 23 times more likely to acquire customers, 6 times as likely to retain customers, and 19 times as likely to be profitable as a result. These are statistics that should be of concern to any organization that is still living a past where data was not that important and gut instinct is the primary decision-making determinant (Hamari, J., & Koivisto, 2015). Even those organizations that used to get away with instinctive decisions are now realizing that they cannot sustain their success with such an approach without considering the possibilities of data.

Another advantage of relying on objective data is that it allows for the successful transition of the organization from one phase to another without significant disruptions (Bansal, 2013). The systems and BI within the organization can be maintained even when the lead participants or employees are no longer with the organization That means that those organizations that are able to successfully leverage the competitive advantages of data science are able to maintain a good level of consistency over the long run (Hair, J. F., Celsi, M., Ortinau, D. J., & Bush, 2010). They are not subject to fluctuations in performance based on the probability of having good or bad luck (Kim and Jeon, 2013). Companies that wish to achieve longevity and sustainability in their operations should leverage the competitive advantages of data science as much as possible. Using data allows everyone to understand what they are doing and why they are doing it (Helmreich, 2000). By understanding the implications of their decisions, managers are more prudent and will ensure that they are acting in the interests of the organization over the long run (Helmreich, 2000). Data allows the players in an organization to understand what is happening in the internal and external environment (Ifinedo, 2016). Because this data is provided on a real-time basis, they are not caught off guard by trends that start occurring unexpectedly (Ifinedo, 2016). Through leveraging the competitive advantages of data science, it is possible to ensure accountability and transparency across the organization (Ulloth, 1992). Everyone knows that the others are doing and how they affect the immediate operations (` and Wood, 1993). That can create a spirit of healthy competition that ultimately benefits the organization (Holmes, 2005). The response from employees can have significant benefits from the organization if they feel that they have access to all the information that they need to do their work (Dutse, 2013). First of all, it can increase engagement because the workers are also part of the solution to the problems that are identified (Hamari et al., 2015). When sales are down, it is not just the concern of the organization or its senior executives (Howells and Wood, 1993). Even the lowliest support employee will take an interest because the information chain has added them to the loop (Min et al., 2008). Even more importantly, data science can provide employees with possibilities of helping to intervene in order to deal with a corporate problem (Lewis, 1996). For example, if the organization is on the brink of bankruptcy; it may so happen that all departments start to cut back on their expenditure in an effort to ensure that this eventually does not occur (Howells and Wood, 1993). This is very different from an organization where everything is done in secret by the senior executives (Jibril and Abdullah, 2013). That means that the average employee will either not buy into the strategic plan or will actively buy out from that strategic plan (Malathy and Kantha, 2013). Others may seek to sabotage the company because they feel that they are not part of the positive aspects that are taking place in that organization (Wallace, 2004).

The organization as a whole can become very proactive because decisions are made on the latest information which is carefully curated and organized so that it has relevance to the priorities of the organization (Dutse, 2013). Employees are part of the solution and will ideate certain ideas that can change the organization towards a better orientation based on the feedback that is coming from the environment (Hair, 2010). Over time, this will mean that the brand will construct a reputation for resilience and responsiveness (Little, 2002). Consumers are always enthusiastic about brands that seem to go that extra mile in order to deal with the emerging needs and expectations of their clients (Kees et al., 2015). Data-driven organizations have the additional advantage of obtaining feedback from their customers about how they are doing and some of the measures that they could take in order to make their services even more appealing to their clients (Holmes, 2005). This is very different from those reactive organizations that only deal with customer issues when there is a serious complaint that threatens to destroy their reputation within the industry (Howells and Wood, 1993). Leveraging competitive advantages of data science means that the organization can make fast and confident decisions that can be defended in any arena and in any situation (Ifinedo, 2016). This is different from those organizations that take decisions that are not based on defensible and therefore the organization is constantly second-guessing itself (Ifinedo, 2016). When organizations are making decisions based on gut instinct, it can take some time before the decision-maker is comfortable making the call (Holmes, 2005). This is particularly true if they are self-conscious enough to understand that they could be subject to biases which render their decision inappropriate (Ifinedo, 2016). However, if the decision is made based on objective data; things become relatively quicker and straightforward (Jansen et al., 2008). These efficiencies and the decisiveness of the organization contributes to its relationship with customers who are more likely to stick with the brand because it has values, but at the same time is able to adjust its performance depending on the feedback that is being sent out by the customers (Ifinedo, 2016).

Data are now woven into every sector and function in the global economy (Bansal, 2013; Helmreich, 2000). Just like other essential factors of production such as hard assets and human capital, much of modern economic activity simply could not take place without them (Chesbrough, 2005; Holmes, 2005; Kim and Jeon, 2013). The use of Big Data will become the basis of competition and growth for individual firms (Chesbrough, 2005; Engelberger, 1982; Howells and Wood, 1993). These are large pools of data that can be brought together and analyzed to discern patterns and make better decisions (Davis et al., 2014; Helmreich, 2000; Mosher, 2013). This offers a number of advantages including enhancing productivity and creating significant value for the world economy (Bansal, 2013; Chiu et al., 2016; Hamari et al., 2015). This is achieved by reducing waste and increasing the quality of products and services (Bachman, 2013; Dutse, 2013). Until now, the torrent of data flooding our world has been a phenomenon.

That probably only excited a few data geeks (Bachman, 2013; Hamari et al., 2015; Helmreich, 2000). But we are now at an inflection point. According to research from the MGI and McKinsey and Company's Business Technology Office, the sheer volume of data generated, stored, and mined for insights has become economically relevant to businesses, government, and consumers (Bansal, 2013; Hilbert and Lopez, 2011). The history of previous trends in IT investment and innovation and its impact on competitiveness and productivity strongly suggest that Big Data can have a similar power (Bansal, 2013; Jansen et al., 2008; Carr, 2010). This is in effect the ability to transform our lives (Helmreich, 2000). The same preconditions that allowed previous waves of IT-enabled innovation to power productivity are in place for Big Data (Bachman, 2013; Ellison, 2004; Holmes, 2005). These include technology innovations followed by the adoption of complementary management innovations (Davis et al., 2014; Hamari et al., 2015; McFarlane, 2010). Consequently, we expect suppliers of Big Data technology and advanced analytic capabilities to have at least as much ongoing impact on productivity as suppliers of other kinds of technology (Dutse, 2013; Hilbert and Lopez, 2011; Mieczakowski et al., 2011). All companies need to take Big Data and its potential to create value seriously if they want to compete (Bachman, 2013; Hamari et al., 2015; Jibril and Abdullah, 2013). For example, some retailers embracing big data see the potential to increase their operating margins by 60% (Hair, 2010; Zhang and Chen, 2015). The companies that will benefit most from the competitive advantages of data science are the ones that recognize the limitations of the old approach (c et al., 2013; Hair, 2010).

1.5 Data engineering practices

Data engineering is a technical process that is responsible for ensuring that the benefits of data science are fully experienced within the organization (Bachman, 2013). We already know that data drives most of the business activities in our contemporary world (Gibson and Brown, 2009). Typically, the organization that is thinking of adopting a data-driven approach will have a number of business questions and problems that need to be resolved satisfactorily before that organization can take its place within the industry (Helmreich, 2000). One of the questions will seek to understand where the business growth is and what is it worth to acquire one more customer in a given segment (Hamari et al., 2015). The company will be looking at possible improvements and then subject them to a cost-benefit analysis in order to assess whether it is worth their while to engage in such activities. Ideally, the organization will engage in the production of output that is most appealing to the consumers that they are targeting (Engelberger, 1982). The adoption of different data engineering business practices is meant to ensure that the answers to these questions are put into practice (McFarlane, 2010). One of the ways in which data engineering business practices are enacted in an organization is through the development of different systems which end up becoming data production units (Awang et al., 2013). The data is the narrative of all the activities that take place within that system as well as the environment dynamics that affect that narrative (Gilks, 2016). Therefore, data engineering business practices are meant to ensure that there is a way of constructing and understanding a narrative of what happens in any given production or operational unit within an organization (Ifinedo, 2016). We may, for example, consider how the customer service system can start generating data for the organization (Hair, 2010). First, there will be the account information for each customer including their name, address, and biographical details (Helmreich, 2000). This is then supplemented by a database of their ordering and payment activities which includes shipments, cancellations, and orders (Jibril and Abdullah, 2013). Another system may consider their relationship with the organization in terms of any customer care complaints that they may have raised (Howells and Wood, 1993). There may yet be another database of psychometric properties which maps consumer behavior, bearing in mind the fact that the customer may have alternative concerns and possible connections with other organizations that provide the same or similar output when compared to the company that is undertaking the data analysis (Howells and Wood, 1993). When all this data is aggregated, the business will have a well-rounded picture of the customer so that they can provide appropriate services to them (Davis et al., 2014). It can also be of benefit to develop a sustainability framework to ensure that the customer will remain with the company over the long run (Hamari et al., 2015). The data sets that comprise this record are independent of each other, but data engineering business practices ensure that they are interlinked and those relationships are clearly mapped out in a way that can help to make decisions (Noughabi and Arghami, 2011). Without appropriate protocols that underpin data engineering business.

practices, it becomes difficult to answer challenging questions about consumer behavior (Davis et al., 2014). Already, it is clear that those organizations that are able to understand and use the data will be at a significant advantage when compared to those that have a much more lackluster performance on this issue (Gilks, 2016). The challenges of managing data can affect any company at any level. We know that even the smallest companies have an enormous amount of data to contend with and this data can be stored in very large repositories (Lyytinen et al., 2016). The interlinkages can become so complex that they overwhelm the system and will, therefore, lead to a breakdown if there is no sufficient infrastructure to support them (Menke et al., 2007). One of the key roles of the data engineering business practices is to ensure that there is facilitation for analysis (van Deursen et al., 2014). This facilitation makes life easy for the data scientists, analysts, and executives that need to make decisions based on that data (Zhang and Chen, 2015). The output from the data engineering business practices must be reliable, fast, and secure so that it provides the optimum support to the decision-maker (Helmreich, 2000). Data engineering must source (Hamari et al., 2015), transform (Ifinedo, 2016), and analyze data from each system (Mosher, 2013). For example, data stored in a relational database is managed as tables, like an Excel spreadsheet (Kim and Jeon, 2013). Each table contains many rows, and all rows have the same columns (Mosher, 2013). A given piece of information, such as a customer order, may be stored across dozens of tables (Menke et al., 2007).

There are other approaches to data engineering business practices which are dependent on the operational requirements of each unit that is working on the issues (Hair, 2010). For example, data stored in a NoSQL database such as MongoDB is managed as documents, which are more like Word documents (Hilbert and Lopez, 2011). Each document is flexible and may contain a different set of attributes (Kees et al., 2015). When querying the relational database, a data engineer would use SQL (Howells and Wood, 1993). This is different from MongoDB which has a proprietary language that is very different from SQL (Ruben and Lievrouw, n.d.). Data engineering works with both types of systems, as well as many others, to make it easier for consumers of the data to use all the data together, without mastering all the intricacies of each technology (Miller, 2014; Ulloth, 1992; van Deursen et al., 2014; van Nederpelt and Daas, 2012). The take-home from such requirements activities is the fact that even the simplest questions may require significant data engineering business practice changes in order to find the right answers (Davis et al., 2014). In order to optimally work with each system, the decision-maker must have some understanding of the data and the technology that they will be dealing with (Hair, 2010). This understanding can be achieved through specific training, development, and coaching (Holmes, 2005). Others may also supplement their competencies through practice knowledge (McFarlane, 2010). Experience can be a great asset to the decision-maker and that is why it is imperative to allow members of staff to engage with the data engineering business practices on a regular basis (Rachuri et al., 2010). Often, setting up the system is the hardest task and things become considerably easier when all is said and done.

The trends and history of data engineering business practices is a long one and which reflects the changing priorities for the main actors within the sector (Dutse, 2013). As companies become more reliant on data, the importance of data engineering continues to grow (Holmes, 2005). Since 2012, Google searches for the phrase have tripled for example (Chiu et al., 2016). There is an increased awareness about the potential of data and the various ways that it can be used in order to strengthen the position of various businesses within a given industry (Hair, 2010). The sheer volume and complexity of Google searchers indicate that even consumers are looking for information as they make their purchasing their decisions (Jibril and Abdullah, 2013). If laypeople can take the effort to search for data before making decisions, what about organizations that have entire departments which are dedicated to research and development? It is not just purchasing decisions that are being done after online searches (Ellison, 2004). We know that there is an exponential increase in job searches on an annual basis and that this trend intensifies during period of economic instability (Helmreich, 2000). Companies in the modern era must take an interest in the search trends that relate to data engineering because it can be one of the ways in which best practice can be shared more widely (Helmreich, 2000). Besides, the fact that data is now a valuable resource means that companies are very protective of it (Gibson and Brown, 2009). Accessing the best data may require more expenditure and other resources (Kim and Jeon, 2013). Companies are finding more ways to benefit from data (Berker et al., 2006; Jansen et al., 2008; Lyytinen et al., 2016). They use data to understand the current state of the business (Berker et al., 2006; Mosher, 2013). They are also using data to predict the fuure (Howells and Wood, 1993), model their customers (Ifinedo, 2016), prevent threats (Sin, 2016), and create new kinds of products (Noughabi and Arghami, 2011). Even as the data itself and the process for collecting it becomes complicated, the data engineering business practices must focus on ensuring that the ultimate output is easy to understand and use (Engelberger, 1982). It is important to acknowledge the need to break down data into components that make it easier for the decision-making process (Howells and Wood, 1993). Eventually, data science will cease to be the exclusive domain of technical people, but a concern that touches on every segment of the organization (Lewis, 1996). Indeed, those that are put in positions which require decision-making will make an effort to ensure that they rely on data since they will have known from experience the kinds of benefits that that approach can bring (Lewis, 1996).

1.6 Applied data science

The interest in applied data science is based on the kinds of benefits that multiple corporations have received from using it as the basis of decision making (Chiu et al., 2016). There is some skepticism about applied data science in general, with some wondering whether it is a passing fad that will not transform the industry over the long run while others consider it to be a once-in-a-lifetime opportunity that can change the future prospects of a business if it is handled well in the present (Evans, 2009). Existing literature has espoused a range of perspectives concerning the utility of applied data science, with varying degrees of veracity (Jibril and Abdullah, 2013). However, there is no doubt that this remains one of the major forces in the industry today (Kees et al., 2015). The benefits of applied data science speak for themselves and they are the justifications for implementing the various programs that are meant to enhance data-based decision making (Berker et al., 2006). There are different levels of application from the most basic to the most advanced (Gibson and Brown, 2009). The business or decision-maker will determine at which level they wish to conduct their analysis and application (Ifinedo, 2016). Moreover, applied data science has a bright future that includes many as-yet-unknown elements that should help businesses significantly if they position themselves as data-driven organizations (Malathy and Kantha, 2013). It is not just a question of having access to data science, but also being able to use it intelligently (Ellison, 2004). Part of this might be to carefully select those situations that require reliance on data science while utilizing some of the other capabilities that the organization has in different situations (Helmreich, 2000). For example, a database may be able to predict consumer behavior, but all that information is nearly useless if there is no customer relationship representative to build up the connections that acquire, service, and maintain a customer (Howells and Wood, 1993). The unintelligent use of data imagines that it is the only solution to every problem that the organization is facing (Kobie, 2015). Besides, the data that is collected is not only designed to be kept for a rainy day, but must be actively utilized before it begins to lose its relevance (Gilks, 2016). Intelligence use data analysis to know about which mix of variables is most likely to bring out the best in a business situation

(Howells and Wood, 1993). Some companies also make the mistake of neglecting the issue of execution (Hair, 2010). It all very well knows what needs to be done, but you will only get results if you are able to actually do the things that are required (Ifinedo, 2016). It is not enough to profess knowledge about consumers if you are not taking active steps to address some of the issues that those consumers are raising about your output (Jibril and Abdullah, 2013). Remember that consumers are human beings with their own perspectives and behavior which may be so complex that you cannot reduce it to a few formulas that are presented in a data pack (Holmes, 2005). The organization that is going to dominate the future will be engaged in a constant search for knowledge in order to cement and expand its current situation (Kim and Jeon, 2013). Over time, organizations have restricted themselves to a small menu through the new socialization and the successful advertising campaigns by some dominant brands (Gilks, 2016). For example, Google has been such a successful search engine that it has spawned a verb that seeks to encompass all search activities (Ifinedo, 2016). In reality, there are many alternatives which could even serve the organization better (Min et al., 2009). For example, it is possible to get localized results from other providers such as Yahoo, Bing, Ask, AOL, and Duckduckgo (Min et al., 2008). Because Google dominates the market so comprehensively, these smaller search engines have started to specialize and it is precisely that specialization that you may be looking for (McFarlane, 2010). If you can create a niche for yourself, it might be a better fit than if you are competing with many other players on a giant search engine (McFarlane, 2010). Remember that Google on average processes more than 20 petabytes worth of data on a single day (Miller, 2014). That is a lot of processing, but it is also processing that is rather generic (McFarlane, 2010). You as the service provider may be looking for localized searches that are visited by a select group of people that may even have passed the first ring of inclusion by signing up to the search engine (Holmes, 2005). If you have, the product that they are looking for, your path towards making a full purchase will be much easier than if you are flooding the internet with content about products that millions of other providers can offer; sometimes at even better terms (McFarlane, 2010). The important thing to take away is that you have to open your horizons rather than restricting them to the most aggressive purveyor of a specific type of applied data science (Gilks, 2016). The savvy consumers are doing it and there is no reason why equally savvy businesses cannot go down the same route (Hilbert and Lopez, 2011).

It is also useful to be able to recognize data science when you see it (Helmreich, 2000). Some companies are so focused on the bottom line that they do not take the time to truly understand their environment and what it means (Howells and Wood, 1993). Initially, data is represented as a sea of details that may not make particular sense in your situation (Menke et al., 2007). The savvy entrepreneur will be able to curate that data and select the trends that are relevant to the field that they wish to explore (Kees et al., 2015). They will then turn that data into highly sophisticated decision- making frameworks that are based on evidence as well as detailed analysis (Jibril and Abdullah, 2013). Let us take the example of digital advertisements that may be released by competitors. It makes sense for a business that is seeking to penetrate a particular market to try and understand how the more experienced firms have been doing their business (Hair, 2010). The entrepreneur should know the differences between a targeted advertising campaign and one which re-targets consumers that have already interacted with the brand in some way (Kees et al., 2015). There is an entire spectrum of digital activities that go into making this advertising campaign work (Lyytinen et al., 2016). All of them are driven by data science as well as the more niche field

of ML (Jibril and Abdullah, 2013). The challenge for the entrepreneur, who wishes to make inroads, is to be able to map out how the entire campaign has been put together (Dutse, 2013). They will be looking at strengths which they can mimic and enhance in their own campaign (Ifinedo, 2016). They may also be looking for weaknesses that need to be mitigated in order to provide their own campaign with the best chance of success in the future (Kobie, 2015). Obviously, this is highly specialized work that will require the services of a dedicated team that can tease out all the aspects that need to be addressed (Noughabi and Arghami, 2011). Beyond the complex algorithms that eventually display on the screen as an advertisement, there are real human efforts and relationships that must be included in the calculus about what is going to take place in a specific campaign (Hair, 2010). It is because of advanced data science that digital ads are able to attract a lot of attention and conversions by a click when compared to traditional advertising (Helmreich, 2000). These are digital adverts that have been carefully calibrated based on the data that is available and high-level analysis that can support the decision-makers in terms of the design and execution of the final display for the consumer (Ifinedo, 2016). The advert will also have gleaned a lot of information about consumer behavior which is then manifested by the ways in which the campaign is eventually allowed to progress (Spiekermann et al., 2010). Sometimes the targeting is so detailed that the advertising is personalized to individuals who are most likely to purchase the product (Gibson and Brown, 2009). This type of specialization is not possible without applied data science (Hilbert and Lopez, 2011). Another innovation that is being used for marketing purposes is the implementation of a recommender system for consumers (Little, 2002). When people make purchases, the predictive analytics will tell the seller about the other complementary or supplementary products that might be of interest to the person (Kirchweger et al., 2015). Therefore, they receive a short notification about the availability of these products on the premise that they are more likely than the average visitor to purchase the recommended products (Berker et al., 2006). Tracking consumer behavior can be controversial because it appears to be a very intrusive form of big data (Lyytinen et al., 2016). However, many organizations are exploring the possibilities of this type of applied data science (Sobh and Perry, 2006). Image recognition has emerged as a potentially controversial but very useful form of applied data science (Gilks, 2016). We are beginning to train machines to recognize faces and that means that a lot of the surveillance that use to be undertaken by law enforcement officers can now be passed on to machines within an acceptable tolerance of error (Ifinedo, 2016). For example, close circuit television cameras are being updated with artificial intelligence that recognizes faces of known offenders who have outstanding warrants (Hilbert and Lopez, 2011). That means that they can easily be apprehended for walking down the street as opposed to the traditional searches that were once undertaken by law enforcement officers (Malathy and Kantha, 2013). Perhaps the problem with this particular type of technology is emblematic of the wider problems that are associated with applied data science (Lyytinen et al., 2016). When the face recognition cameras were put in place, there were trial runs that showed a very high error rate (Malathy and Kantha, 2013). This is an error rate that the public considers to be unacceptable, even for those people that have a criminal record (Carlson, 1995). Some worry that a government that is capable of monitoring every aspect of our lives is one that is too powerful to be held accountable (Kirchweger et al., 2015). Private companies are also using this technology in ways that could be harmful to private individuals (Gilks, 2016). For example, a user can upload their image with friends on Facebook and then start getting suggestions to tag known and assumed friends (Zhang and Chen, 2015). This automatic tag suggestion feature uses face recognition algorithm. However, some of the people that are tagged may no longer be in touch or willing to be friends with the person (van Deursen et al., 2014). Similarly, while using WhatsApp web, you scan a barcode in your web browser using your mobile phone (Davis et al., 2014). Google provides you the option to search for images by uploading those (Chiu et al., 2016). It uses image recognition and provides related search results. All these are useful developments, but one which also have serious ethical implications (Bansal, 2013; Min et al., 2009). Other applications that have gained in popularity include speech recognition software which can be used to improve the social functionality of people with speech impairment or other related disability (Hilbert and Lopez, 2011). It can also be linked to other password-protected systems, therefore reducing the time that it takes to complete an authentication procedure (Mosher, 2013). Some of the best examples of speech recognition products is Google Voice, Siri, and Cortana which are very popular with young executives (Hamari et al., 2015). Those who are unable to or unwilling to type down text can still use technology through speech recognition. In that sense, this type of applied data science is helping to expand access (Malathy and Kantha, 2013). Of course, those that have used speech recognition fully understand the fact that it can never completely replicate the sophistication of a human brain. That is why some really strange translations can take place when relying on this type of technology (Lewis, 1996). Despite some misgivings, the applied data science relating to consumer interactions with technology have increased (Hilbert and Lopez, 2011). Nowhere is this more felt than in the gaming industry. EA Sports, Zynga, Sony, Nintendo, and Activision-Blizzard have led gaming experience to the next level using data science (Miller, 2014). Games are now designed using ML algorithms which improve and upgrade themselves as the player moves up to a higher level (Mieczakowski et al., 2011). Motion games allow for comparative analysis of competitor performance in order to elicit a competent response from the current player (Jansen et al., 2008). Similarly, price comparison websites are constantly looking for ways to incorporate applied data science into their own operations (Menke et al., 2007). At a basic level, these websites are being driven by lots and lots of data which is fetched using APIs and RSS Feeds (Jansen et al., 2008). PriceGrabber, PriceRunner, Junglee, Shopzilla, and DealTime are some examples of price comparison websites (Noughabi and Arghami, 2011).

1.7 Opening up the perspective of the decision maker

The starting point is the decision is routinely made based on the knowledge and experience of the person that is making the decision (Awang et al., 2013). This is actually the wrong approach in the age of data science (Hilbert and Lopez, 2011). There is so much information coming out, that it seems a waste if it is ignored in favor of what the decision-maker things they know (Evans, 2009). It is highly recommended and even essential that the decision-maker is always open to listen to the data science (Kim and Jeon, 2013). From that, they can start to weigh all the options before settling on the ones that seem to achieve their business goals (Holmes, 2005). If they refuse to acknowledge the contribution of data science, they are actually short changing themselves (Min et al., 2008). Another mistake that decision-makers commit is to perceive data science from one perspective or one disciplinary framework (Bachman, 2013). Big data has an advantage in as far as it comes from a multiplicity of sources that should enrich the basis on which business decisions are made (Evans, 2009). The ability to access and interpret this data for optimum effect on the corporate goals is what is known as decision intelligence (Kees et al., 2015).

It is a phenomenon that is even present in the animal kingdom. For example, lions must glean very many aspects of their environment whilst on the hunt in order to foil the prey's effort to escape them. Academia has also started to take an interest in decision intelligence in order to understand why some executives are so much better than others when it comes to making critical decisions. Decision intelligence is actually a multifaceted concept that is studied from a multidisciplinary perspective which includes social sciences, applied data science, management, and even economics (Ellison, 2004). This is in effect one of the vital sciences today which has a number of applications including contributing to the development of artificial intelligence that is uniquely geared towards the needs of the organization (Gilks, 2016). The issue that might call for specific attention is the recruitment of staff members that are competent enough to handle the more complex aspects of the data science (Gilks, 2016). Even where there is a skills gap, it can be covered using translation skills (Kobie, 2015). Some researchers actually suggest the data science can help decision-makers to set goals, objectives, and metrics that will be used to assess performance (Kobie, 2015). Data science today is mainly automated and therefore one of the tasks will be to ensure that there is harmonization of systems during the transitional phase (Kirchweger et al., 2015).

Decision intelligence is the discipline of turning information into better actions at any scale (Dutse, 2013). A number of firms may have access to the same information, but it is only the truly competitive ones that will know how and when to use it (Hamari et al., 2015). The data deluge means that there is plenty of information out there and that it is accessible to those that are willing to search for it (Helmreich, 2000). The companies that decide to pay for their analysis will get a somewhat better picture than those that rely entirely on open science outlets (Hilbert and Lopez, 2011). Regardless of whether or not the data is paid form, there is an impetus to engage in strategic thinking about which data is important and how it is important (Kim and Jeon, 2013). Producing or reading substantial reports that have little relevance to the decision-making scenario is counterproductive because it wastes resources (Kirchweger et al., 2015). The real data that needs to be worked on may even be hidden behind the various technical aspects that are picked into the report (Kirchweger et al., 2015). The strategic organization will ruthlessly discard that information that is not relevant or outdated in favor of current relevant information that can be used for forecasting (McFarlane, 2010). Overall, data science has played a critical role in opening up the perspectives of decision-makers in a variety of organizations (Ifinedo, 2016). It does not matter whether they are the most senior executive in the organization or a lowly support worker. Data science is still relevant to them and it can make them a more effective employee.

1.8 Properly evaluating feasible options

In order to make good decisions, one must be able to evaluate the alternatives before selecting the ones that are most workable in the circumstances (Awang et al., 2013). Unfortunately, there are many decision-makers that are simply in a rush to get things done (Evans, 2009). They do not ruminate on the choices available to them and as a consequence make hasty decisions that are not supported by the evidence (Gilks, 2016). Data science can serve the role of focusing the decision-maker on the evidence (Jibril and Abdullah, 2013). They are then in a position to identify those solutions that best address the problems that have been identified in the brief (Miller, 2014). There may be many options that are not easily identified but which are actually quite useful for solving the problems that the business or individual encounters (Menke et al., 2007). The most successful modern businesses have embraced big data because it contains some of the options that were previously hidden from them (Holmes, 2005). Indeed, some of the data may be provided on an open science basis which does not cut into the bottom line (Jibril and Abdullah, 2013). This means that the company only needs to identify those information strands that are relevant to it and then use them accordingly (Noughabi and Arghami, 2011). Startups, in particular, can benefit from this arrangement because they tend not to have a large research and development budget (Jansen et al., 2008).

Expanding the options on which a final decision is made can bring about many benefits (Chiu et al., 2016). First of all, it allows the business to leverage its wealth or investment funds appropriately based on those projects that are most likely to yield a high return with manageable risk (Gilks, 2016). The fact that data science is digitized means that this information is at your fingertips (Hilbert and Lopez, 2011). Stockbrokers have embraced data science for this reason because it opens up their ability to creatively configure an investment portfolio for purposes of maximizing the income that an investor can get (Jansen et al., 2008).

At the same time, this approach allows them to calculate and mitigate risks which can dent any profits that are made (Jibril and Abdullah, 2013). It is collectively known as business intelligence (BI), but so many businesses fail to take full advantage of the benefits that data science can bring to their decision making (Kim and Jeon, 2013). Businesses that consider all options are able to attain commercial growth in a way that is sustainable by leveraging their best resources to target the most lucrative opportunities that exist within their environment (Evans, 2009). This is not something that is only experienced when dealing with the external environment (Little, 2002). It can also be used to make decisions about the organization and re-organization of internal departments for the purposes of improving the bottom line and achieving organizational evolution (Mieczakowski et al., 2011). For example, there may be departments that are not really performing well and need to be put under certain measures in order to get the best out of them (Ulloth, 1992). In order for all these benefits to be realized, organizations must implement the right reporting tools (Evans, 2009). They can monitor and evaluate them on a regular basis in order to identify where the data gaps are (Helmreich, 2000). The personnel that make decisions as well as prepare reports must be trained so that they are able to optimize their analysis in ways that are conducive to achieving the stated business goals (Howells and Wood, 1993). Accuracy and other aspects of data quality are of the essence (Mosher, 2013). The organization should set aside a budget for ensuring that the data on which decisions are made is of the highest possible quality (Trottier, 2014). Existing literature talks about tangible insight as a much better approach to business decisions making than gut instinct. The tangible insight arises from knowing what is really going on and how it affects your business (Hamari et al., 2015). It is not a theoretical construct without practical value. Indeed, some of the more advanced data analyses allow you to engage in scenario mapping so that you can compare the expected outcomes of each type of decision that you make (Hilbert and Lopez, 2011). Businesses that have adopted tangible insight as the default decision-making model are more likely to succeed and sustain their success than those that are merely founded on gut instinct alone (Kobie, 2015). Besides, it can be problematic identifying the person with the best gut instinct (Hilbert and Lopez, 2011). Typically, the owner will take on this role despite the fact that they may not have as much information about the business environment as other members of the team (Noughabi and Arghami, 2011). It is an arbitrary way of making decisions and in most cases might turn out to be detrimental to the prospects of the business (van Deursen et al., 2014). This is not about removing the entrepreneur from the decision-making process (Holmes, 2005). Rather, it is about streamlining and cleaning up the decision-making process so that it is rational and can withstand the test of time (Kees et al., 2015). Indeed, those businesses that have adopted a data-driven approach to decision making can build resilience through carefully studying the consequences of past and present decisions (Jibril and Abdullah, 2013).

1.9 justification of decisions:

Some business leaders have adopted a managerial style that is closer to an empire than a fully functioning business process (Hamari et al., 2015). They make all the decisions and are not accountable to anyone (Helmreich, 2000). This is particularly true where the chief executive officer of an organization is also its owner (Little, 2002). Small and medium-sized businesses fall into this category (Miller, 2014). Because they do not have to report to anyone about the decisions that they make, these leaders mistakenly believe that they need not justify their decisions (Ulloth, 1992). In fact, all business decisions must be justified by a rationale that is based on business data (Wallace, 2004). It is even better if these justifications are written down so that those who inherit the roles can understand what happened and the consequences of what happened (Bansal, 2013). Making justified decisions can bring about investment capital inflows since potential investors are attracted to those entities that are very clear about why they are taking particular courses of action (Holmes, 2005). This is different from businesses that typically look inward for capital financing and do not feel that they have to be accountable to their creditors and investors (Menke et al., 2007). Once again, it is a disease that afflicts the small and medium-sized businesses that tend to also have a high failure rate (Min et al., 2008).

One of the excuses that are sometimes provided by entrepreneurs when they do not want to justify their decisions is the fact that they have to make quick decisions which do not allow for reflection (Helmreich, 2000). However, that is a self-created crisis (McFarlane, 2010). There is plenty of big data out there and if the organization gets into the habit of regularly checking that data, the entrepreneur will already have background information that can support their decision making (Little, 2002). Urgency can be a justification for certain decisions, but it is not an excuse for not reviewing the data (Wallace, 2004). Indeed, even after a quick decision has been made; it is still possible to revisit the data to understand whether that was the right decision or not. Although it may be too late for the hastily made decision, it can prevent future problems because the decision-maker will have learnt from their mistakes (Noughabi and Arghami, 2011). The data science modalities that are on the market today can also cope with fast decision making since they provide information in real-time upon request (Helmreich, 2000). All that an executive has to do is check their smartphone and they will have important data that can impact on their decision making (Holmes, 2005). It is even possible to have a dedicated analyst that is consulted when decisions are being made (Little, 2002). Of course, the sense of urgency must be properly communicated because some analytics will continue working slowly and deliberately without recognizing the costs to the company if they do not keep pace with what is happening (Menke et al., 2007). When making data-driven decisions, executives sometimes complain that they are not provided with the kind of guidance that they hoped for (Engelberger, 1982). The reports are either too detailed or too obscure (Howells and Wood, 1993). Others are merely looking for quick summaries that give them quick answers to complex problems (Jibril and Abdullah, 2013). It is important for executives to recognize the fact that the data analysis tends to be guided by the research brief that is provided by the client (Howells and Wood, 1993). This research brief may be a broad document that is used in a generic way or it could be specific when a problem arises and the decision-maker wants all the possible answers (Min et al., 2008). The complexity of the problem dictates the pace of responding and the complexity of the answer (Noughabi and Arghami, 2011). Therefore, executives must calibrate their thinking in ways that align with the kinds of business problems that they are presenting to the analyst (Min et al., 2009). The analyst does not actually make the final decision (Min et al., 2008). They merely support the decision-making process by presenting pertinent data (Ulloth, 1992). Nevertheless, data science reports must be presented in formats that are accessible and understandable to the decisions makers (Hilbert and Lopez, 2011). They are a persuasive decision-making tool and these reports cannot fully maintain that role if they are not clear or do not speak to the issues that are important to the decision-maker (Lewis, 1996). It is also important to avoid overwhelming the decision-maker with multiple reports that are sometimes self-contradicting (Lyytinen et al., 2016). The reality is that managers tend to switch off if they are given a mini data deluge by a data analyst that does not know how to curate information is that it is the most relevant to the situation (Lewis, 1996). That does not mean that the analyst is required to massage the data in order to tell the client what they want to hear (Zhang and Chen, 2015). Data science speaks for itself and does not need to be embellished in order to carry its message across (Wallace, 2004). In any case, many of the things that will be highlighted in the report are factually and cannot be changed by subjective negative feelings about them. Instead, the business should take corrective, preventative, and precaution actions against negative outcomes that are highlighted in the report (Mieczakowski et al., 2011).

We have already hinted on the benefits of maintain records of the rationale that underpins decisions that are based on data. This is very important for those companies that hope to survive beyond the exit of the original executives (Hilbert and Lopez, 2011). It should be an implicit goal of an organization to ensure that it can survive its founders (Holmes, 2005). Otherwise, there would be multiple businesses that open and close the moment that their creators are no longer engaged with them (Miller, 2014). A durable business will be based on systems and procedures that can outlast changes in personnel (Ruben and Lievrouw, n.d.). Data science is part of the durability and it has been implicated in succession planning for some of the larger organizations (Gibson and Brown, 2009). Maintaining records is also a form of accountability to the stakeholders in the business who may include the owners, creditors, employees, and customers (Miller, 2014). This comes into play when there is a query about the decision which has been taken or when the decision has led to some unexpected negative consequences (Bansal, 2013). A record shows that the people who took the decision acted rationally and based on the information that was available to them at the time (Mieczakowski et al., 2011). Keeping a record of all these transactions can play a role in helping to track decision and also support those who take over from the old guard (Miller, 2014).

This is not about creating unnecessary layers of bureaucracy as would be the case in a public sector organization (Holmes, 2005). Rather it is about telling a story without gaps so that those who follow can continue that story (Jansen et al., 2008). It can also become an accountability measure for those that have a stake in the business to understand that the decisions which are consequential in that organization are never taken arbitrarily (Menke et al., 2007). The government as a regulator of the business environment may also be interested in understanding how decisions are made just in case there are questions of liability (Min et al., 2008). Good record-keeping might save the organization from fines or other legal penalties if they have taken a decision that is later found to be incompatible with the administrative regime in that locality (McFarlane, 2010). It is not just about keeping all the raw data for later reference. The analyst must chart their sources and the processes that they used in order to come to a final decision (Little, 2002). Besides, it might be useful to consider the alternatives so that the decision can be reconfigured if the feedback from the environment calls for such a response (Noughabi and Arghami, 2011). The record of data-driven decisions then ends up being a strong narrative about the operations of the company (Kees et al., 2015). This will give lenders, owners, and customer's confidence that the business is on the right footing and can survive in the future (Min et al., 2008).

1.9 Less subjectivity and more objectivity in decision-making

it is fitting that the conclusion to this book focuses on the core role of data science in decision making (Hilbert and Lopez, 2011). Good data science reduces the subjectivity that exists in business and instead promotes some level of objectivity (McFarlane, 2010). Perhaps this is an offshoot of the ontological and epistemological positioning of data science in which the methodologies emphasis an objective truth that can be gleaned through carefully organized research (McFarlane, 2010). Some might argue that subjectivity is inevitable in business since it is people that make the business (Stone et al., 2015). We know that human beings have their own biases and socialization which affect the way in which they view the world or respond to it. The imposition of strict objectivity on such a world might be counterproductive. On the other hand, we also know that data science is one of the many variables that contribute to the success of a business (Menke et al., 2007). Therefore, in rely on data science; decisionmakers are engaging in a form of triangulation which moderates the biases of the human decision-makers with the objective data that is coming out of the environment (Mieczakowski et al., 2011).

There are arguments to be had about whether or not objectivity is better than subjectivity in decision making. However, the evidence shows that data-driven organizations are able to survive in many business environments and that they do this by relying on information about those environments in order to make decisions (Howells and Wood, 1993). That has been the premise of this book and it should be the premise of all decision making in any given organization (Jibril and Abdullah, 2013). Intuition and other subjective measures are important, but they should not be the only consideration (Miller, 2014).

Section 2. Business Intelligence

2.1 Definitions

While business intelligence is relatively a recent terminology, the first work highlighting the importance of collecting information for economic purposes dates back to the First World War. Other historical facts also point out that information collection was already carried out in the wharves of ports on newly arrived sailors. “Under the reign of Louis XIV, the official envoys of the kingdoms of France, England and Spain already called upon the systematic collection of economic, political, social and strategic information to inform their monarch, not only about the state forces of the enemy but also on the state of its economy”(Harbulot, C., & Baumard, 1997). It was in 1918 that the German engineer Siegfried Herzog wrote the book *The Future of German Industrial Exports* in order to anticipate the country’s economic policy after the end of the war by creating a “commercio-industrial federation” for collecting information and using it to preserve the competitive advantage of the German industry (Herzog, 1919). In the mid 19th century, Japan began to collect and process information at the national level, highlighting the importance of information and considering it a “collective resource to be fully exploited” .In 1979, Michael Porter emphasized the effect of information technology on competitive advantage. In the book *Competitive Strategy: Techniques for Analyzing Industries and Companies*, he speaks explicitly of the term “competitor intelligence system” (Porter, 1980 p. 72). Thus, BI began to emerge in the economic world and made its official appearance in France in February 1994, following the recommendations in a report by the group "BI and Business Strategy," chaired by Henri Martre (Martre, 1994 p. 3). It was only in 2006 that business intelligence was mentioned in an official speech of the Algerian government (Fekir, 2009).

Decision-making can be properly done through the appropriate decision support systems (Dillon et al., 2010) and with the information provided (Watson & Wixom, 2007; Hočevar & Jaklič, 2008). As a result, using the information system will function as a competitive advantage for organizations (Rezaei et al., 2011). In the same context, Turban et al., (2011) argue that the use of information technology is vital for organizations in the way that it possesses capabilities that facilitate DMPs. Turban et al., (2011) went further by emphasizing the importance of computerized decision support systems, such as the BI tools.

In literature, BI has multiple definitions. According to Azvine et al, (2006), BI is not well defined; this means that some consider it to be data reporting while others talk about business performance management. Furthermore, database analysts emphasize data extraction while analytics highlight the analysis of statistics and data mining (Azvine et al., 2006). In the same context, since decision-makers no longer trust the KPI nor the dashboards (Azvine et al., 2006), BI is changing the way companies are managed, decisions are made and employees perform their jobs (Watson & Wixom, 2007).

As a result, BI is "All about how to capture, access, understand, analyze and turn one of the most valuable assets of an enterprise—raw data—into actionable information in order to improve business performance" (Azvine et al., 2006, p.2).

BI includes technologies and applications employed in the use of several financial and non financial metrics, key performance indicators to assess the present state and the method of deciding future course of action for a business.(Hari, 2007).

BI means leveraging information assets within key business processes to achieve improved business performance (William & William, 2007).

The definition that explains the concept of BI follows:

"Business intelligence consists of the processes, tools, and technologies required to turn data into information and information into knowledge and plans that drive effective business activity" (Eckerson, 2003, p. 49).

As a result, and according to Eckerson (2003), BI is like an oil refinery that converts raw material—crude oil—into the refined material—gas oil. This means that BI converts data into knowledge and this is done through a process cycle (Eckerson, 2003).

2.2 The Business Intelligence history

In 1856, Richard Miller Devens talks about BI in his Encyclopedia of Commercial & Business Anecdotes. He looks for how to obtain intelligence that will lead to a successful business. Thus, he knows about the market issues before his competitors.1958 Hans Peter Luhn published an article called "A Business Intelligence System," in which he outlined the basics of a BI system in a sketchy diagram. When documents entered to the system, it undergoes a process before actions took place. 1960 the data increased and became difficult to manage and to get knowledge from. Thus something new needed to be developed. 1970 Siebel and IBM entered the world of modern BI. At that time, BI became a must have for many organizations.1990 During these years BI became big money but unfortunately it needed to extract the most valuable knowledge from the big data. 2000 BI users extracted the valuable information from data. Moreover, more technologies were used that supported decision-making.2018 BI nowadays represents a powerful tool that organizations have. BI has many functions and provides the organizations different benefits. As a result, BI information and knowledge are used for sales, marketing, finance, planning and decision making.

2.3 The Business Intelligence Architecture

Turban et al (2011) define BI as "an umbrella term that combines architectures, tools, databases, analytical tools, applications, and methodologies" Rouse (2018), however, defines BI architecture as a framework by which the data, information management and the components of technology are organized for building BI systems. Moreover, Ong et al., (2011) argue that BI architecture includes the types of data that need to be collected and the method used to analyze those data to present the information needed. According to Ong et al., (2011), the layer of metadata should be included in BI architecture. A good BI architecture should include a layer of metadata which is important to storing and monitoring data (Ong et al., 2011). Moreover, Table 1 presents the BI architecture according to Ong et al., (2011).

Table 1.BI Architecture and Layers (Ong et al., 2011)

Layers	Definition

Data Source Layers	Data can come from internal or external sources. An internal data source means that the data come from inside the organization. These data are related to information concerning customers, sales and products. External data sources are related to competitors, the market and the external environment of the organization.
Extract–Transform–Load (ETL) Layer	Extract means taking the most relevant data that support decision making. Transform means to convert data into a special format that is suitable for reporting. Load is the final phase. The data are loaded into the target repository.
Data Warehouse Layer	This layer contains three components: operational data store, data warehouse, and data marts. Operational data store integrates all data that come from the ETL and put it in a data warehouse. The data warehouse represents the central storage of data from internal and external resources. The data are stored for between 5 and 10 years and is updated regularly. Data marts play the support role for the data warehouse and provides specific departments with the needed information, which the data warehouse cannot do.
Metadata Layer	This layer describes the data. This means that it shows how data are stored, from where they were extracted, the changes that happen to the data and so on. examples of metadata layers include the following: OLAP: This describes the structure, level and dimension of the data that Enable
	the user to extract the needed data. Data mining: Its role is to analyze the data to extract the most useful information from it (Witten &Frank, 2000) Reporting metadata: It is used to store reports names and reports

	description.
End User Layer	This layer shows the tools that are used to represent the information needed by the users. It describes the level where such tools are used. In each level, specific BI tools are used to extract information.

2.4 The Business Intelligence Benefits

Since BI aims at focusing on creating value by looking for knowledge (Sabherwal & Fernandez, 2010), organizations use BI to achieve a variety of benefits such as profitability, reduced costs, and efficiency (Isık et al., 2013). In the same context, Sabherwal & Becerra-Fernandez (2010) grouped BI benefits into 3 major categories: improvement of operational performance, improvement in customer relations and the identification of new opportunities in contemporary organizations.

“Key benefits that business intelligence aims to create are the increased efficiency and effectiveness of the organization” (Hočevar & Jaklič, 2008, p. 94). This means that BI enables the organization to improve its internal processes to have a competitive advantage and to thus meet the needs of the market.

2.4.1 Increased staff productivity:

BI enables the staff to work independently and with more autonomy. In that context, Carver and Ritacco (2006) argue that BI allows its users to access databases wherever it is stored and to have the ability to prepare reports to get to know the organization’s situation.

2.4.2 Reduction in costs of effective decision-making:

“With business intelligence, we can find the causes of certain problems as well as to identify and to analyze the key success factors” (Hočevar & Jaklič, 2008, p. 95). They go further by arguing that with the use of BI, effective decisions can be made (Hočevar & Jaklič, 2008).

In the same context, Carver and Ritacco (2006) state that the quality of decisions has a direct relationship with the costs. As a result and to improve decision quality, organizations should provide their staff the appropriate means to make decisions (Carver & Ritacco, 2006).

2.4.3 Reduced operational costs

Williams and Williams (2003) state that “The business value of BI lies in its use within management processes that impact operational processes that drive revenue or reduce costs, and/or in its use within those operational processes themselves”

Conclusion

Whereas Business Intelligence uses data with high information density to measure things or detect trends. Big data can in fact transform how decision makers view business problems overall and shape decisions that concern strategy. This then allows them to rely upon objective data.

Data-driven decision making is an essential process for any professional to understand, and it is especially valuable to those in data-oriented roles. For novice data analysts who want to take a more active part in the decision-making process at their organization, it is essential to become familiar with what it means to be data driven.

One of the biggest reasons why businesses need to use analytics to make better decisions is due to the risk being posed by the sheer amount of data being gathered

. There is so much unstructured data being delivered that it’s easy to make the wrong decisions unless it’s properly analyzed. With that said, having the right data analytics strategy in place will predict risk and help make better decisions moving forward.

Business analytics also makes expansions much less risky since businesses have access to valuable information before they make their final decision. It’s also possible to interact with the information so that it can be used to create an actionable plan.

Companies that have a baseline standard for measuring risk are going to be able to incorporate exact numbers into their decision modelling process. In short, they can predict certain scenarios and plan for them in advance.

CHAPTER 2

DATA VISUALISATION TECHNIQUES AND BIG DATA TOOLS

Introduction

There's a growing demand for business analytics and data expertise in the workforce.

The use of common data visualization techniques helps to implement the data-driven decision-making-process, including increased confidence and potential cost savings. Learning how to effectively visualize data could be the first step toward using data analytics and data science to the advantage of adding value to the organization.

Several data visualization techniques can help to become more effective. Here are 14 essential data visualization techniques all professionals should know, as well as tips to help effectively present the data.

It is common to think of data visualization as relatively modern developments in statistics. In fact, the graphic portrayal of quantitative information has deep roots. These roots reach into histories of the earliest map-making and visual depiction, and later into thematic cartography, statistics and statistical graphics, with applications and innovations in many fields of medicine and science which are often intertwined with each other. They also connect with the rise of statistical thinking and widespread data collection for planning and commerce up through the 19th century. Along the way, a variety of advancements contributed to the wide-spread use of data visualization today. These include technologies for drawing and reproducing images, advances in mathematics and statistics, and new developments in data collection, empirical observation and recording(Chen et al., 2008)

Data visualization is the process of creating graphical representations of information. This process helps the presenter communicate data in a way that's easy for the viewer to interpret and draw conclusions.

There are many different techniques and tools to visualize data, here are some of the most important data visualization techniques

Section 1. Data visualization

1.1 Pie Chart

Pie charts are one of the most common and basic data visualization techniques, used across a wide range of applications. Pie charts are ideal for illustrating proportions, or part-to-whole comparisons.

Because pie charts are relatively simple and easy to read, they're best suited for audiences who might be unfamiliar with the information or are only interested in the key takeaways. For viewers who require a more thorough explanation of the data, pie charts fall short in their ability to display complex information.

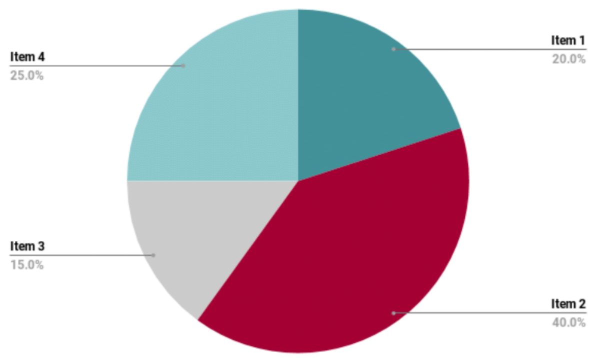


Figure 2.Example of a typical pie chart.

1.2 Bar Chart

The classic bar chart, or bar graph, is another common and easy-to-use method of data visualization. In this type of visualization, one axis of the chart shows the categories being compared, and the other, a measured value. The length of the bar indicates how each group measures according to the value.

One drawback is that labeling and clarity can become problematic when there are too many categories included. Like pie charts, they can also be too simple for more complex data sets.

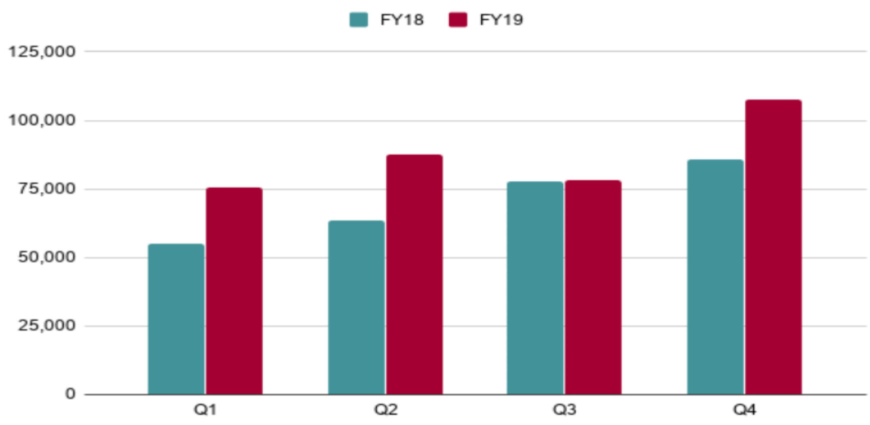


Figure 3.Example of a typical bar chart.

1.3 Histogram

Unlike bar charts, histograms illustrate the distribution of data over a continuous interval or defined period. These visualizations are helpful in identifying where values are concentrated, as well as where there are gaps or unusual values.

Histograms are especially useful for showing the frequency of a particular occurrence. For instance, if you'd like to show how many clicks your website received each day over the last week, you can use a histogram. From this visualization, you can quickly determine which days your website saw the greatest and fewest number of clicks.

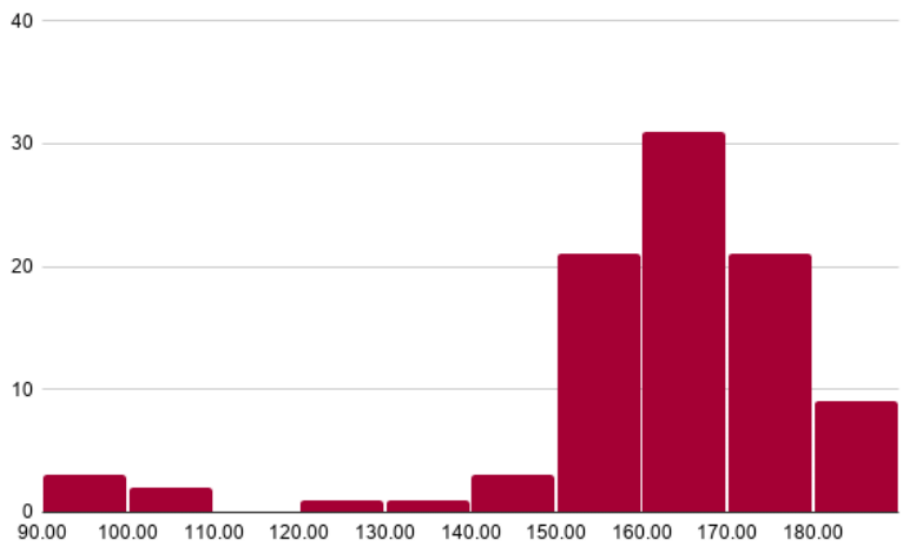


Figure 4.Example of a typical histogram

1.4 Gantt Chart

Gantt charts are particularly common in project management, as they're useful in illustrating a project timeline or progression of tasks. In this type of chart, tasks to be performed are listed on the vertical axis and time intervals on the horizontal axis. Horizontal bars in the body of the chart represent the duration of each activity.

Utilizing Gantt charts to display timelines can be incredibly helpful, and enable team members to keep track of every aspect of a project. Even if you're not a project management professional, familiarizing yourself with Gantt charts can help you stay organized.

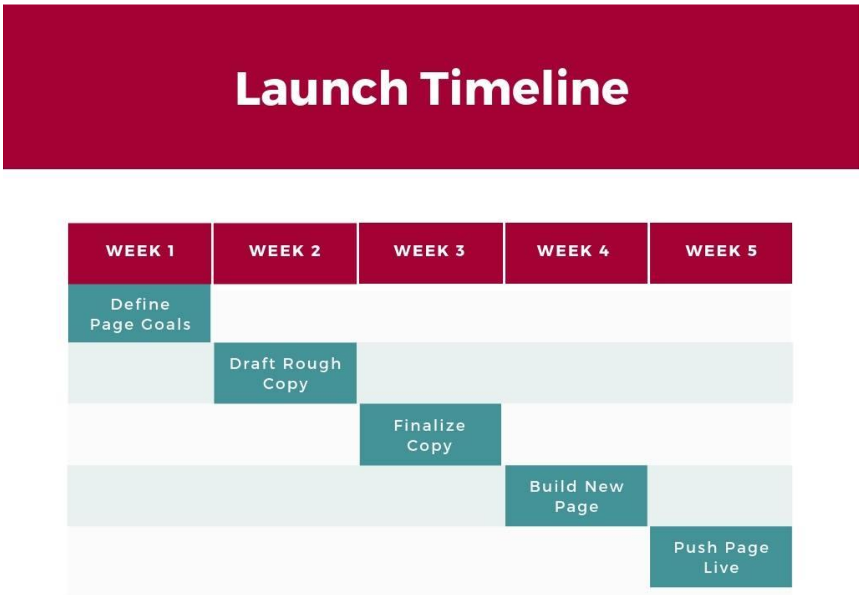
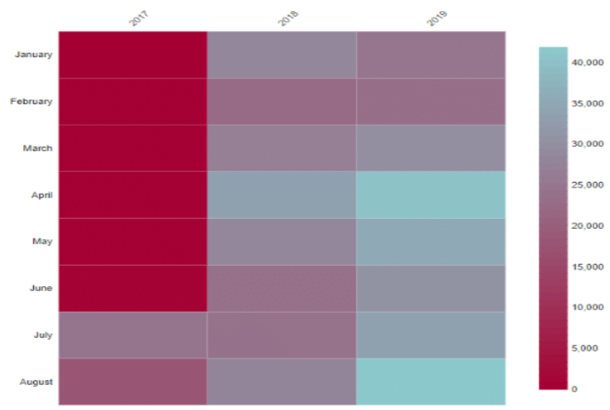


Figure 5.Example of a typical Gantt chart.

1.5 Heat Map

A heat map is a type of visualization used to show differences in data through variations in color. These charts use color to communicate values in a way that makes it easy for the viewer to quickly identify trends. Having a clear legend is necessary in order for a user to successfully read and interpret a heatmap.

There are many possible applications of heat maps. For example, if you want to analyze which time of day a retail store makes the most sales, you can use a heat map that shows the day of the week on the vertical axis and time of day on the horizontal axis. Then, by shading in the matrix with colors that correspond to the number of sales at each time of day, you can identify trends in the data that allow you to determine the exact times your store experiences



the most sales.

Figure 6.Example of a typical heat map.

1.6. A Box and Whisker Plot

A box and whisker plot, or box plot, provides a visual summary of data through its quartiles. First, a box is drawn from the first quartile to the third of the data set. A line within the box represents the median. “Whiskers,” or lines, are then drawn extending from the box to the minimum (lower extreme) and maximum (upper extreme). Outliers are represented by individual points that are in-line with the whiskers.

This type of chart is helpful in quickly identifying whether or not the data is symmetrical or skewed, as well as providing a visual summary of the data set that can be easily interpreted.

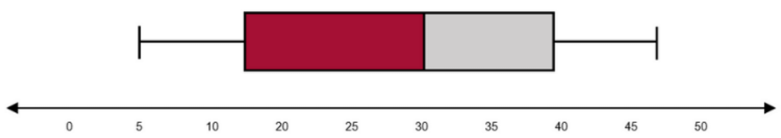


Figure 7.Example of a typical box and whisker plot.

1.6 Waterfall Chart

A waterfall chart is a visual representation that illustrates how a value changes as it's influenced by different factors, such as time. The main goal of this chart is to show the viewer how a value has grown or declined over a defined period. For example, waterfall charts are popular for showing spending or earnings over time.

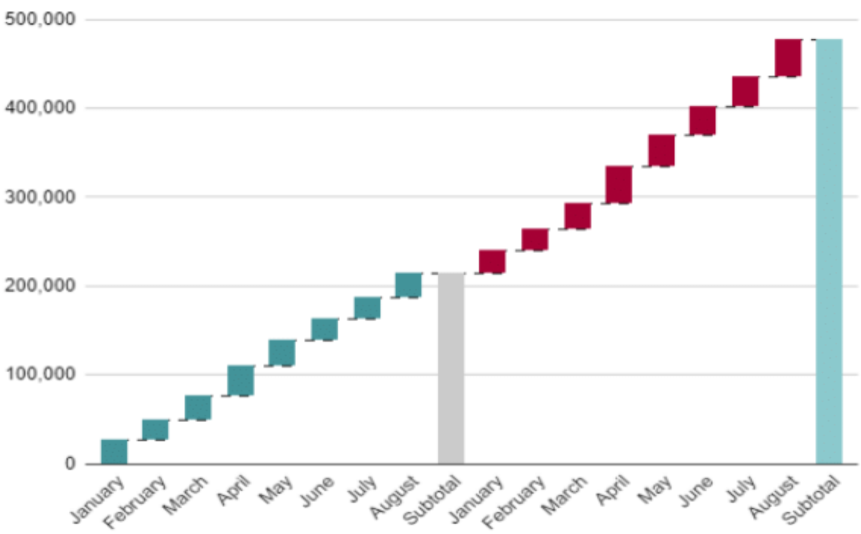


Figure 8.Example of a typical waterfall chart.

1.7 Area Chart

An area chart, or area graph, is a variation on a basic line graph in which the area underneath the line is shaded to represent the total value of each data point. When several data series must be compared on the same graph, stacked area charts are used.

This method of data visualization is useful for showing changes in one or more quantities over time, as well as showing how each quantity combines to make up the whole. Stacked area charts are effective in showing part-to-whole comparisons.

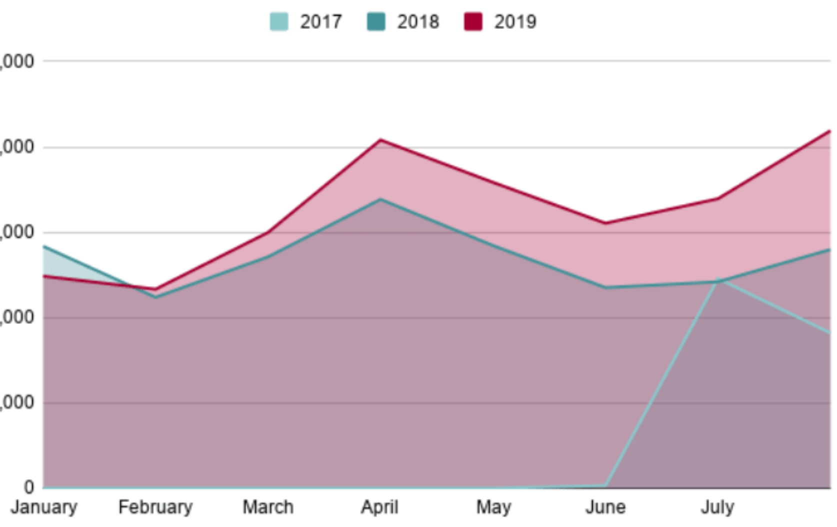


Figure 9.Example of a typical area chart.

1.8 Scatter Plot

Another technique commonly used to display data is a scatter plot. A scatter plot displays data for two variables as represented by points plotted against the horizontal and vertical axis. This type of data visualization is useful in illustrating the relationships that exist between variables and can be used to identify trends or correlations in data.

Scatter plots are most effective for large data sets, since it's often easier to identify trends when there are more data points present. Additionally, the closer the data points are grouped together, the stronger the correlation or trend tends to be.

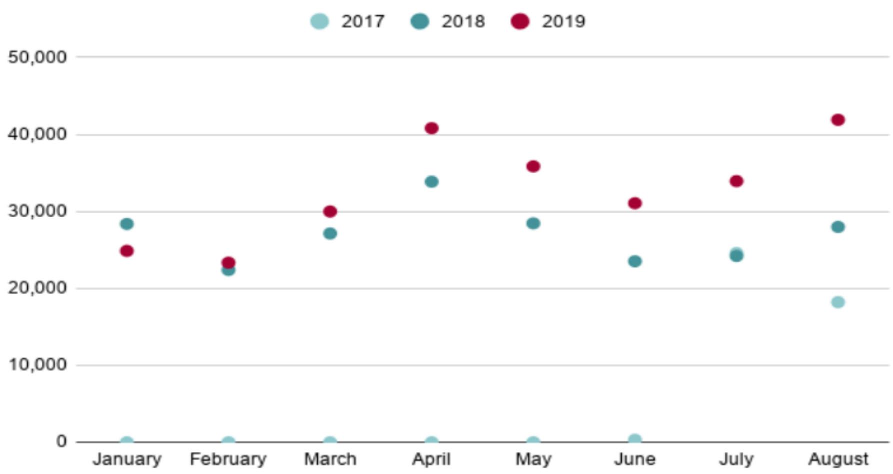


Figure 10.Example of a typical scatter plot.

1.9 Pictogram Chart

Pictogram charts, or pictograph charts, are particularly useful for presenting simple data in a more visual and engaging way. These charts use icons to visualize data, with each icon representing a different value or category. For example, data about time might be represented by icons of clocks or watches. Each icon can correspond to either a single unit or a set number of units (for example, each icon represents 100 units).

In addition to making the data more engaging, pictogram charts are helpful in situations where language or cultural differences might be a barrier to the audience's understanding of the data.

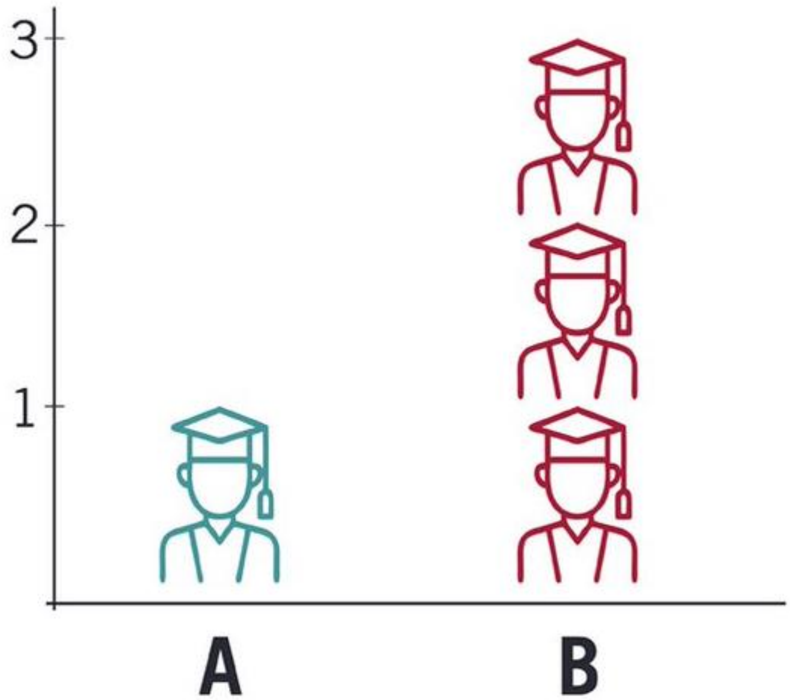


Figure 11.Example of a typical pictogram charts.

1.10 Timeline

Timelines are the most effective way to visualize a sequence of events in chronological order. They're typically linear, with key events outlined along the axis. Timelines are used to communicate time-related information and display historical data.

Timelines allow you to highlight the most important events that occurred, or need to occur in the future, and make it easy for the viewer to identify any patterns appearing within the selected time period. While timelines are often relatively simple linear visualizations, they can be made more visually appealing by adding images, colors, fonts, and decorative shapes.

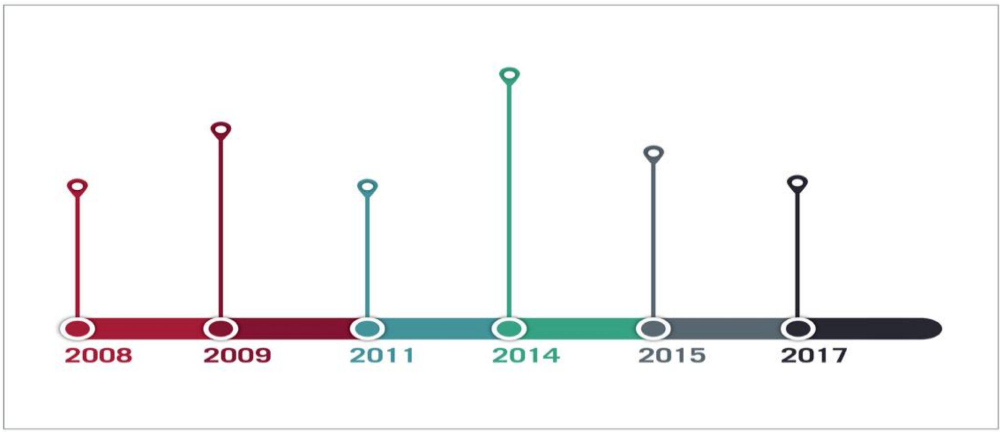


Figure 12.Example of a typical timeline chart.

1.11 Highlight Table

A highlight table is a more engaging alternative to traditional tables. By highlighting cells in the table with color, you can make it easier for viewers to quickly spot trends and patterns in the data. These visualizations are useful for comparing categorical data.

Depending on the data visualization tool you're using, you may be able to add conditional formatting rules to the table that automatically color cells that meet specified conditions. For instance, when using a highlight table to visualize a company's sales data, you may color cells red if the sales data is below the goal, or green if sales were above the goal. Unlike a heat map, the colors in a highlight table are discrete and represent a single meaning or value.

Body Fat Percentage Chart for Men

Lean | Ideal | Average | Above Average

18-20	2	3.9	6.2	8.5	10.5	12.5	14.3	16	17.5	18.9	20.2	21.3	22.3	23.1	23.8	24.3	24.9
21-25	2.5	4.9	7.3	9.5	11.6	13.6	15.4	17	18.6	20	21.2	22.3	23.3	24.2	24.9	25.4	25.8
26-30	3.5	6	8.4	10.6	12.7	14.6	16.4	18.1	19.6	21	22.3	23.4	24.4	25.2	25.6	26.5	26.9
31-35	4.5	7.1	9.4	11.7	13.7	15.7	17.5	19.2	20.7	22.1	23.4	24.5	25.5	26.3	27	27.5	28
36-40	5.6	8.1	10.5	12.7	14.8	16.8	18.6	20.2	21.8	23.2	24.4	25.6	26.5	27.4	28.1	28.6	29
41-45	6.7	9.2	11.5	13.8	15.9	17.8	19.6	21.3	22.8	24.7	25.5	26.6	27.6	28.4	29.1	29.7	30.1
46-50	7.7	10.2	12.6	14.8	16.9	18.9	20.7	22.4	23.9	25.3	26.6	27.7	28.7	29.5	30.2	30.7	31.2
51-55	8.8	11.3	13.7	15.9	18	20	21.8	23.4	25	26.4	27.6	28.7	29.7	30.6	31.2	31.8	32.2
56 & UP	9.9	12.4	14.7	17	19.1	21	22.8	24.5	26	27.4	28.7	29.8	30.8	31.6	32.3	32.9	33.3

Figure 13.Example of a typical highlight table.

1.12 Bullet Graph

A bullet graph is a variation of a bar graph that can act as an alternative to dashboard gauges to represent performance data. The main use for a bullet graph is to inform the viewer of how a business is performing in comparison to benchmarks that are in place for key business metrics.

In a bullet graph, the darker horizontal bar in the middle of the chart represents the actual value, while the vertical line represents a comparative value, or target. If the horizontal bar passes the vertical line, the target for that metric has been surpassed. Additionally, the segmented colored sections behind the horizontal bar represent range scores, such as “poor,” “fair,” or “good.”

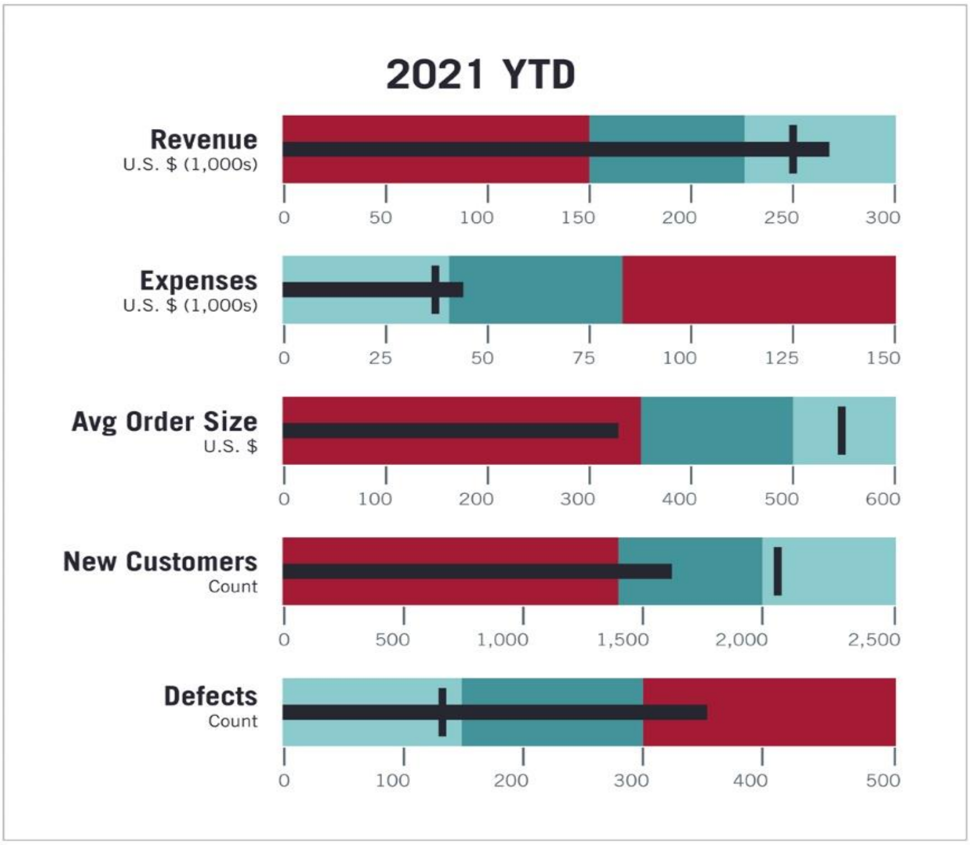


Figure 14.Example of a typical bullet graph.

1.13 Choropleth Maps

A choropleth map uses color, shading, and other patterns to visualize numerical values across geographic regions. These visualizations use a progression of color (or shading) on a spectrum to distinguish high values from low.

Choropleth maps allow viewers to see how a variable changes from one region to the next. A potential downside to this type of visualization is that the exact numerical values aren't easily accessible because the colors represent a range of values. Some data visualization tools, however, allow you to add interactivity to your map so the exact values are accessible.

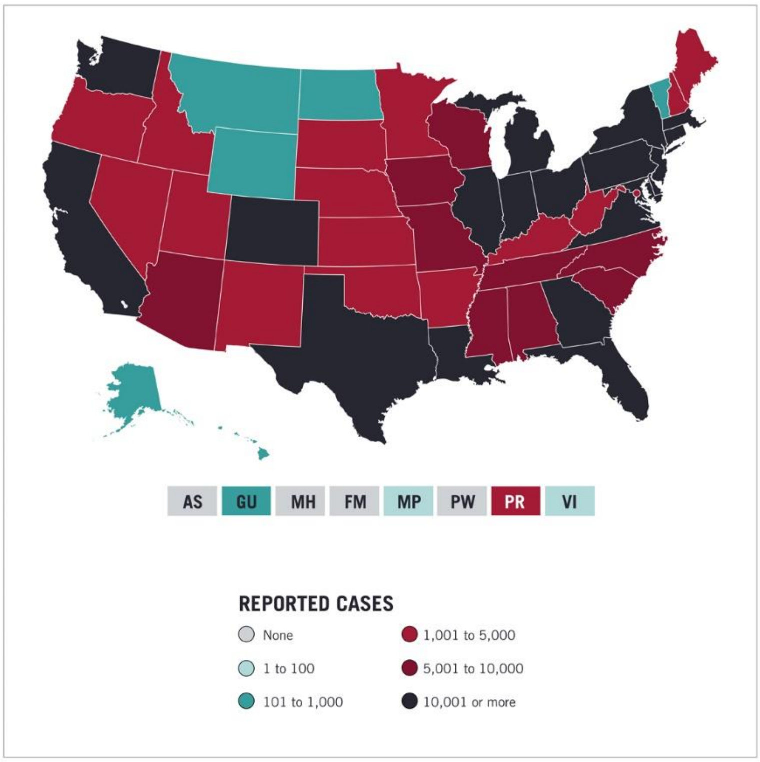


Figure 15.Example of a typical choropleth map.

Section 2: Big Data tools and visualisation

2.1 Big Data tools

One of the simplest and cheapest ways to use Big Data is to track the number of people who are searching a given term each day by using a tool loke Google's Big Query. This is a free service that allows a user to query terabytes of data in seconds using a Structured Query Language (SQL) interface. (SQL is a special- purpose programming language designed for managing data held in a relational data base management systems) These results can be extremely powerful, as demonstrated by the fact that by tracking the search term "flu symptoms" this technique was able to detect regional outbreaks of the flu a week to 10 days before they are reported by the U.S Centers for Disease Control and prevention.

In the age of social networking, public opinion is as likely to be shaped by popular bloggers or those with many followers on Twitter as it is by traditional experts who write for newspapers or magazines. People who have the power to shape the opinions and decisions of others because of their knowledge, relationship, or authority are called influencers. Marketers wish to identify the influencers in order to communicate with them and change their minds, social scientists view them as early indicators of futur public opinion.

One of the simplest tools used to identify influencers is a free service called Klout which measures the size and engagement of a user's social media network based on their activity on Twitter, Facebook, Google+, LinkedIn, Foursquare, and Instagram data to arrive at a social influence or Klout score.

These cores measure the overall influence of a user and range between 1 and 100, with 40 being the average. The disadvantage is that Klout does not alloy out o isolate those who have influence around a specific topic. Marketers and social scientists wish to search for influencers who rank the highest for a specific topic or product ca accomplish this using tools like Little Bird, Inkybee, or Cyfe.

Moving to a more sophisticated level of analysis requires the use of the data-processing tools that have been developed to handle the rapid growth in size of the World Wide Web. Search engines, like Yahoo and Google, were the first companies to work with datasets that were too large for conventional methods. In order to power its searches, Google developed a search strategy called Map Reduce. The software distributes a task onto a multitude of processors which process the input. Traditional data warehouses use a relational database like Excel rows and columns. Search engines need to handle non-relational databases, sometimes called NoSQL. The most popular software to handle NoSQL database is called Hadoop, and several different versions are available as freeware. Hadoop is designed to collect data even if it doesn't fit nicely into tables, distribute a query across a large number of separate processors, and then combine the results into a single answer in order to deliver results in almost real time. Hadoop jobs have traditionally been written in Java, but recently interfaces are being developed that make the process easier for less-experienced operators.

2.2 Data visualisation

Data visualization tools provide data visualization designers with an easier way to create visual representations of large data sets. When dealing with data sets that include hundreds of thousands or millions of data points, automating the process of creating a visualization, at least in part, makes a designer's job significantly easier.

These data visualizations can then be used for a variety of purposes: dashboards, annual reports, sales and marketing materials, investor slide decks, and virtually anywhere else information needs to be interpreted immediately.

The best data visualization tools on the market have a few things in common. First is their ease of use. There are some incredibly complicated apps available for visualizing data. Some have excellent documentation and tutorials and are designed in ways that feel intuitive to the user. Others are lacking in those areas, eliminating them from any list of "best" tools, regardless of their other capabilities.

The best tools can also handle huge sets of data. In fact, the very best can even handle multiple sets of data in a single visualization.

The best tools also can output an array of different chart, graph, and map types. Most of the tools below can output both images and interactive graphs. There are exceptions to the variety of output criteria, though. Some data visualization tools focus on a specific type of chart or map and do it very well. Those tools also have a place among the "best" tools out there.

Finally, there are cost considerations. While a higher price tag doesn't necessarily disqualify a tool, the higher price tag must be justified in terms of better support, better features, and better overall value.

2.2.1 Sisense

Sisense is a business intelligence platform that lets you join, analyze, and picture out information they require to make better and more intelligent business decisions and craft out workable plans and strategies. It is highly flexible for any business size, ranging from startups and developing enterprises to Fortune 500 giants including Sony, ESPN, Comcast, and NASA.

It won our Best Business Intelligence Award for 2020 as well as our 2020 Supreme Software Award. Sisense also currently occupies the highest spot on our list of top 10 business intelligence apps.

With Sisense, you can unify all your data into visually appealing dashboards via a drag and drop interface. Sisense basically allows you to turn data into highly valuable insights and then share them with colleagues, business partners, and clients via interactive dashboards.

Business analytics is easily accessible for each member of your organization as the software ensures easy discovery of business insights regardless of their experience in the field or the complexity of data. Sisense enables you to clean and consolidate data so you can explore and visualize it in a way that brings you valuable insights into your business.

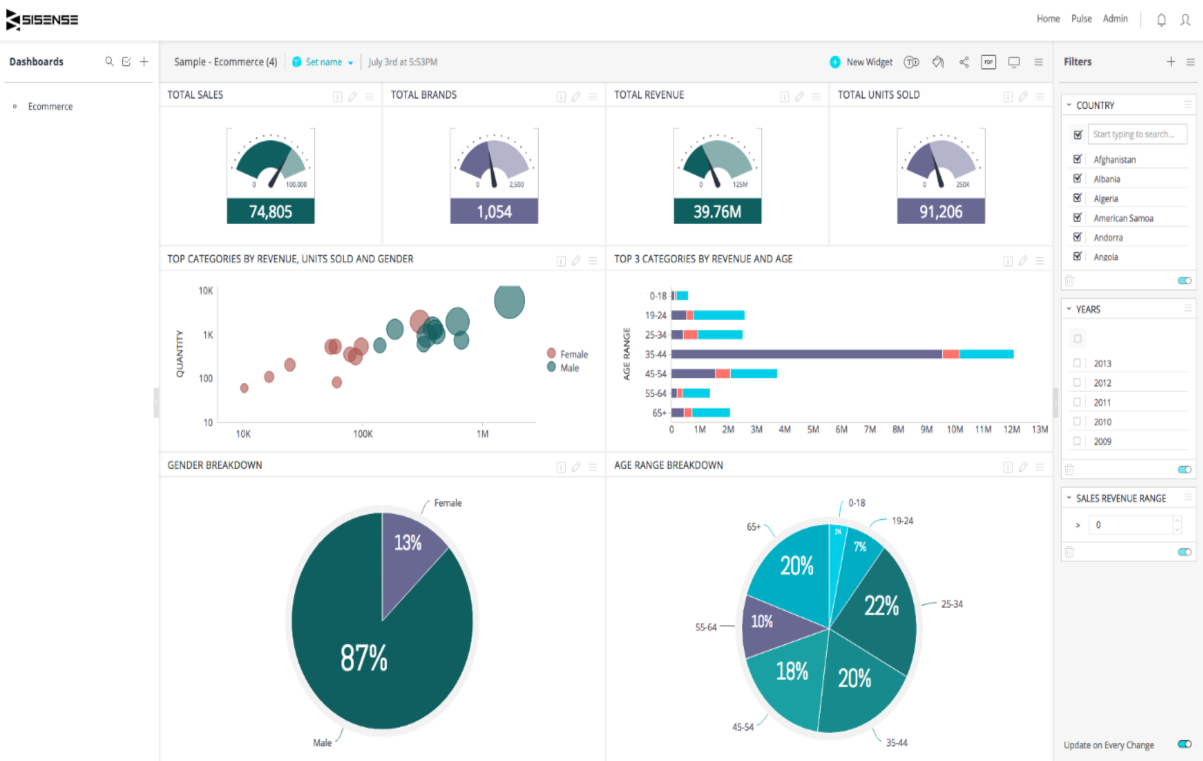


Figure 16.Overview of Sisense

2.2.2 Looker

Looker is a data-discovery app that provides innovative data exploration functionalities for businesses both large and small. With it, they can access a web-based interface where they can easily get real-time insights on their operations via data analytics. They can create reports on the go and make it accessible to all parties interested, so other team members can contribute to discussions about certain tasks and stay in-the-loop when it comes to any development in their project. Thus, Looker can help all companies use data to drive their business decisions and activities in the right direction.

With a little bit of SQL knowledge, you won’t have any issues making Looker work for you or building your own analytic modules. You can design visualizations with a single code, as complexity depends only on how far you intend to go to refine you experience. Looker’s ML code is there to help you produce and optimize your queries, which is particularly handy as most BI systems expect you to be an expert in the area.

Looker still works when you have no SQL knowledge, as they have a rich database of videos and learning materials, the same as live recordings and screen cast lectures. Documentation also includes interactive puzzles which would please creative teams looking to convert analytics into an enjoyable activity.

As you will read in the Benefits section, there is a lot Looker can offer in addition to open API integration blocks and flexible pricing. It analyzes both web-hosted and SQL information, and accommodates over 25 data variations, among which Hive, Vertica, and Google’s BigQuery. The platform is designed to end data chaos and bottlenecks, and does so in an intuitive interface employees take no time to understand. Currently, Looker is the preferred business intelligence application of over 700 companies worldwide, helping them keep customers satisfied and discover how to turn traffic into valuable eCommerce information.

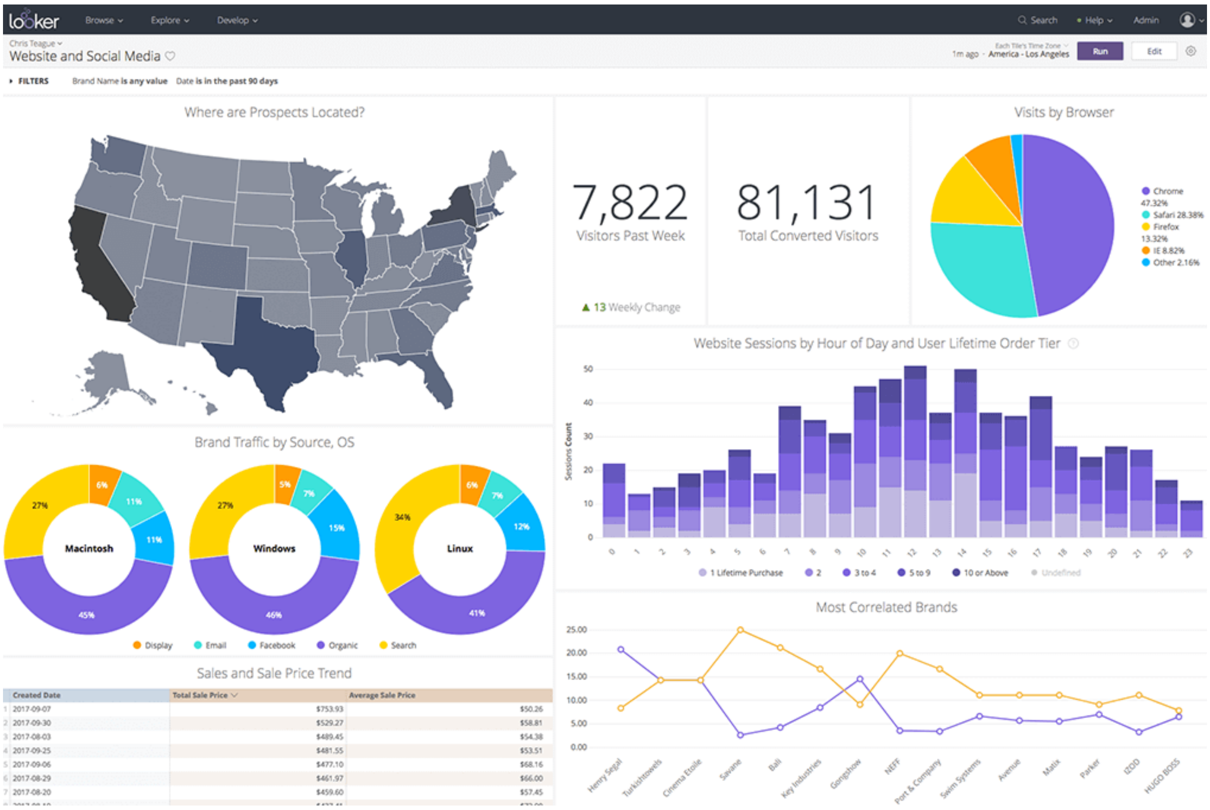


Figure 17.Overview of Looker

2.2.3 Tableau

Tableau is a business intelligence system that helps companies visualize and understand their data. The first place in this category is held by Sisense which has a total score of 9.7/10 and is the winner of our Best Business Intelligence Software Award for 2019. You can try out Sisense for free here. You can also compare Tableau Software with Sisense and see which one is better for your company.

Giving a revolutionary new approach when it comes to business intelligence, the solution allows businesses to quickly connect, visualize, as well as share data with an efficient seamless experience all the way from the PC to the iPad. You can create and publish dashboards, then sharing them with partners, colleagues, or customers—but without the need for programming skills. If you’re already using a Tableau Service (Tableau Online or Tableau Server), there will be no obstacles to let data flow seamlessly from one platform to the other.

Tableau Desktop is a self-service analytics solution that allows you to look at data and answer questions rapidly. Tableau Server enables you to publish dashboards from your Tableau Desktop on any web browser or mobile-based device.

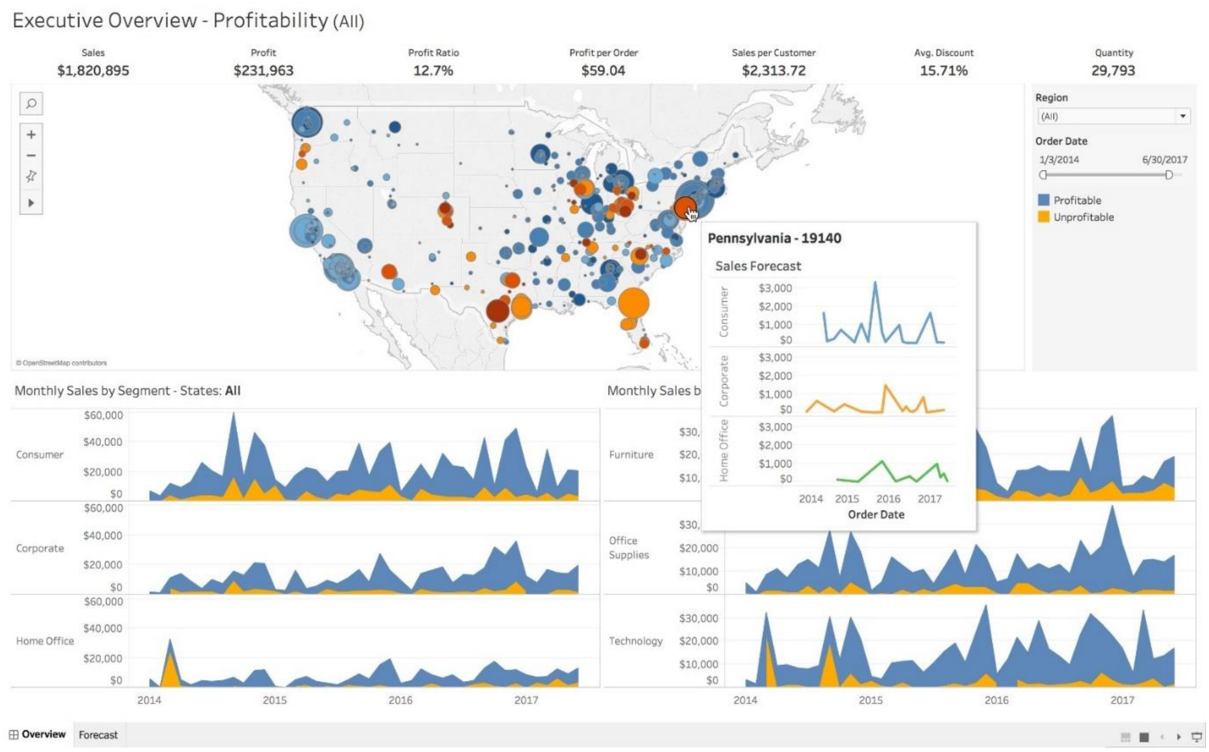


Figure 18.Overview of Tableau

2.2.4 Power BI

Microsoft Power BI is a suite of business analytics tools designed and created to help businesses systematically scrutinize data and share insights. No. 1 spot in this category is held by Sisense which has a score of 9.7 and has won our Best Business Intelligence Software Award for 2019. You can try out Sisense for free here. You can also compare Sisense with Microsoft Power BI and see which one is better for your company.

Microsoft Power BI converts company's data into very attractive and comprehensible visuals, making it easy for you and your company gather information, organize and devise effective business strategies. The system is created so that you stay in the know, to identify trends as they occur, and to steer your business towards success. The platform also helps users track their business and derive answers fast via robust and comprehensive dashboards that are available on every device.

Initially, Microsoft Power BI was planned as an add-in for the Microsoft ecosystem, but it has now evolved into a more fully functional product that sits at the top of the self-service BI market. Self-service business intelligence (BI) tool Microsoft Power BI has proven to be a solid business intelligence platform that already has a large following and support ecosystem.

To make matters even better, Microsoft continues expanding its capacity with new connectors (a MailChimp Database, for instance), in order for users to improve the quality of their campaigns, query directly their Server Query Language databases and Spark data sources.

Just recently, the company launched Power BI Embedded, a new and powerful version with extra reporting capabilities that can easily be embedded into custom developers' apps. What users like the most about this system is the possibility to publish their reports and visualizations directly on the web, so that they can target social media posts and emails, and make them accessible to everyone who may be interested in them.

Alongside Microsoft Power BI, users can also purchase a tool called Personal Gateway used to authenticate additional on-premise data sources currently located outside the firewall. The tool nevertheless functions only on Windows operating systems to enable connection to cloud-hosted analytics.

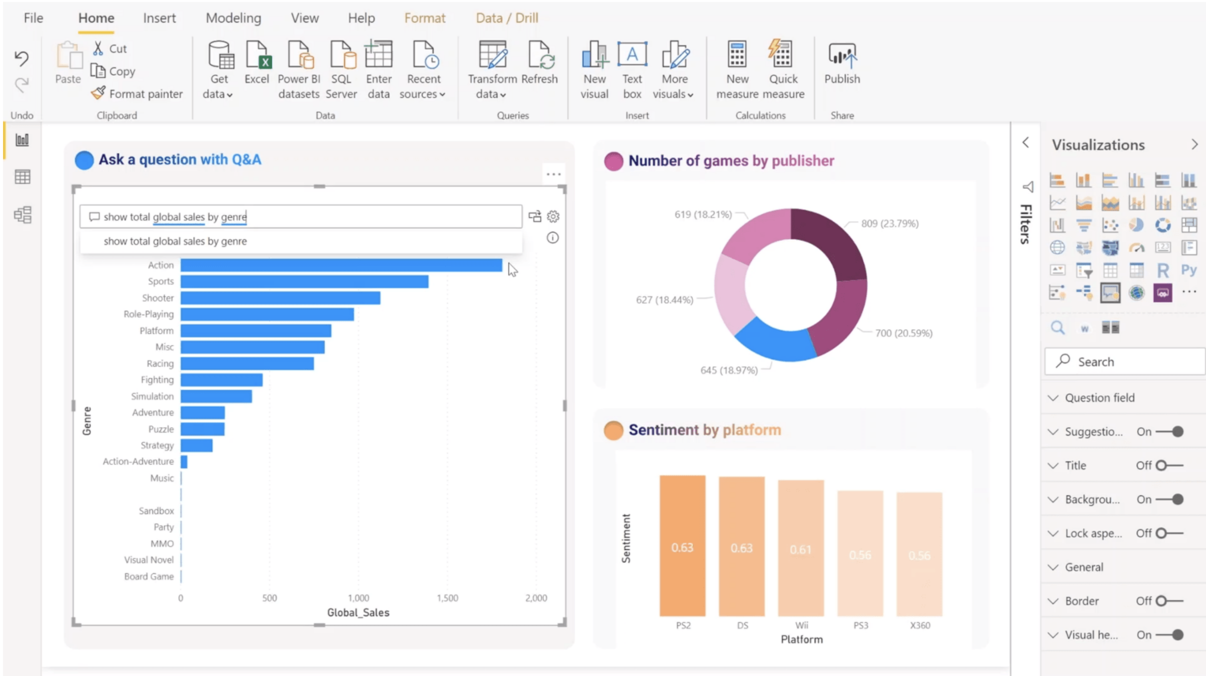


Figure 19.Overview of Power BI

2.2.5 Reveal

Built for embedded analytics scenarios, Reveal is a self-service business intelligence platform that helps you create, view, and share data visualizations and insightful dashboards. It has a user-friendly interface that has drag-and-drop capabilities, intuitive swiping, and a wide array of visualization types.

To help you stay on top of your business performance, Reveal provides interactive reports and real-time dashboards that you can access using any device, be it Android and iOS smartphones and tablets or Windows and Mac desktops.

The platform offers solutions for various processes, including sales, finance, marketing, and operations. It offers real-time insights and KPIs for a data-driven approach in your business processes. You will also appreciate its straightforward and flexible architecture, which allows you to create and analyze dashboards and reports without any advanced technical skills.

In addition, Reveal helps you gain insights and transform them into valuable reports and analytics using its stunning visualization features. It connects and syncs all your data to the cloud or to on-premise SQL databases. In some cases, it also integrates with local Excel spreadsheets in real-time.

The software's embedded BI also allows you to maximize your data visualization and connect them to existing applications. This means you can create custom data visualizations and embed them into your next app. Regardless of the device and location, your dashboards will still have your brand's look and feel, and you can reach your application users through a variety of platform options.

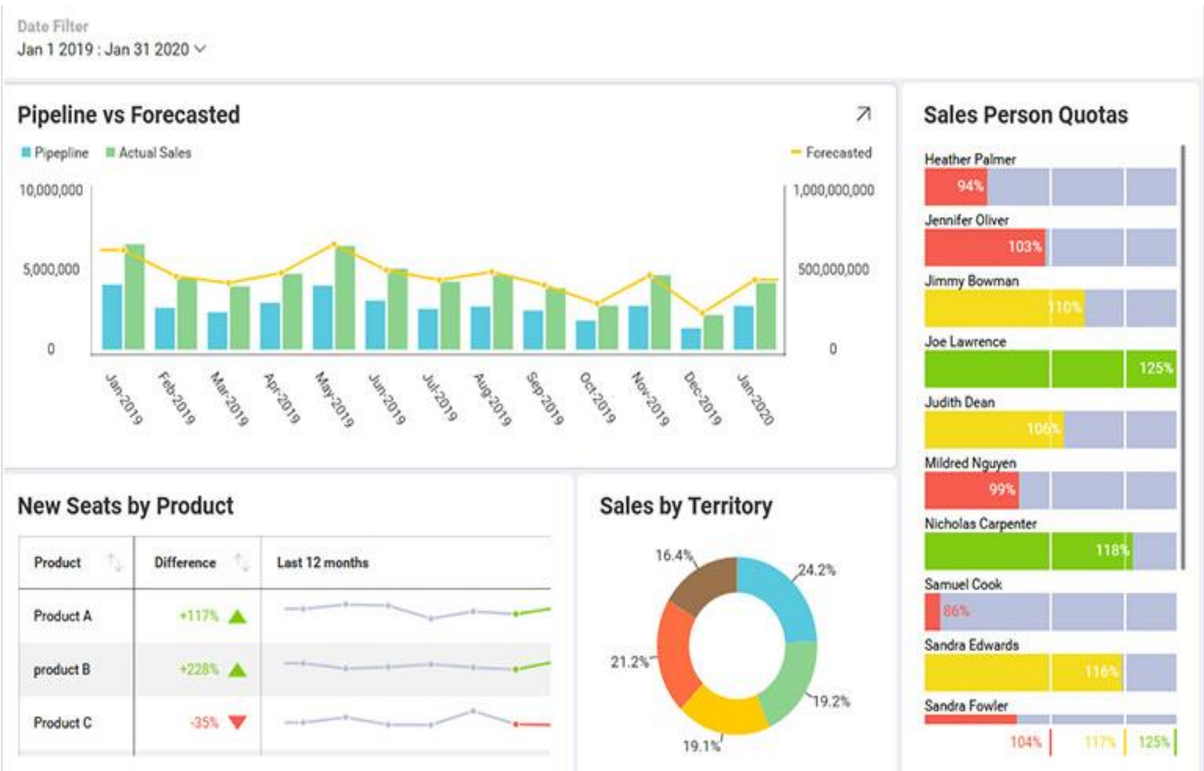


Figure 20.Overview of Reveal

2.2.6 SAP

SAP Analytics Cloud is an integrated platform that simplifies business analytics to enable you to make intelligent and sound decisions at all times. With this solution, you can apply insights into every business process for confident actions.

As SAP Analytics Cloud is built on the SAP Cloud Platform, you can expect to work with a reliable and high performing solution. Thus, you can extract information from your data quickly for accelerated decision-making.

In line with that, the solution also enables the mobile workforce because of its architecture. Since it is cloud-based, users can access SAP Analytics Cloud wherever they are, whenever they need to, and navigate and utilize it on their preferred device.

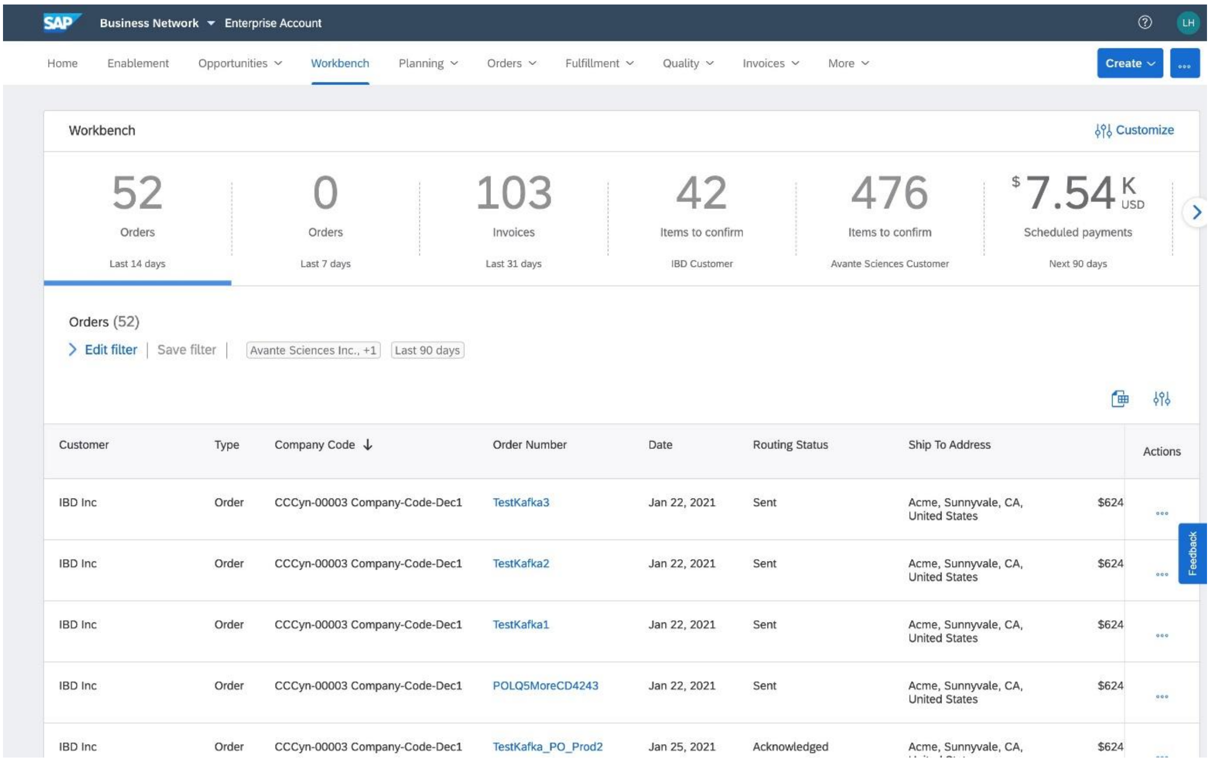


Figure 21.Overview of SAP

Conclusion

Creating effective data visualizations requires more than just knowing how to choose the best technique for your needs. There are several considerations should be taking into account to maximize the effectiveness when it comes to presenting data.

One of the most important steps is to evaluate the audience. For example, if presenting financial data to a team that works in an unrelated department, better to choose a fairly simple illustration. On the other hand, if presenting financial data to a team of finance experts, it’s likely safely include more complex information.

Another helpful tip is to avoid unnecessary distractions. Although visual elements like animation can be a great way to add interest, they can also distract from the key points the illustration is trying to convey and hinder the viewer’s ability to quickly understand the information.

The colors used, as well as the overall design are important. While it’s important that the graphs or charts are visually appealing, there are more practical reasons to choose one color palette over another. For instance, using low contrast colors can make it difficult for the audience to discern differences between data points. Using colors that are too bold, however, can make the illustration overwhelming or distracting for the viewer.

Data visualization is a skill that’s important for all professionals. Being able to effectively present complex data through easy-to-understand visual representations is invaluable when it comes to communicating information with members both inside and outside the business.

There’s no shortage in how data visualization can be applied in the real world. Data is playing an increasingly important role in the marketplace today, and data literacy is the first step in understanding how analytics can be used in business.

CHAPTER 3

DECISION-MAKING

Introduction

Decision making is a daily activity for any human being. There is no exception about that. When it comes to business organizations, decision making is a habit and a process as well. Effective and successful decisions make profit to the company and unsuccessful ones make losses. Therefore, corporate decision-making process is the most critical process in any organization. In the decision-making process, we choose one course of action from a few possible alternatives. In the process of decision making, we may use many tools, techniques, and perceptions. In addition, we may make our own private decisions or may prefer a collective decision. Usually, decision making is hard. Majority of corporate decisions involve some level of dissatisfaction or conflict with another party.

Decision-making is an integral part of modern management. Essentially, Rational or sound decision making is taken as primary function of management. Every manager takes hundreds and hundreds of decisions subconsciously or consciously making it as the key component in the role of a manager. Decisions play important roles as they determine both organizational and managerial activities. A decision can be defined as a course of action purposely chosen from a set of alternatives to achieve organizational or managerial objectives or goals. Decision making process is continuous and indispensable component of managing any organization or business activities. Decisions are made to sustain the activities of all business activities and organizational functioning.

Decisions are made at every level of management to ensure organizational, or business goals are achieved. Further, the decisions make up one of core functional values that every organization adopts and implements to ensure optimum growth and drivability in terms of services and or products offered.

Section 1: Decision-making history and important concepts

1.1 History of decision-making

Most early numbering methods were unwieldy, as anyone knows who has tried to multiply XXIII by VI. The Hindu-Arabic numeral system (which, radically, included zero) simplified calculations and enticed philosophers to investigate the nature of numbers. The tale of our progression from those early fumbling with base 10 is masterfully told by Peter Bernstein in *Against the Gods: The Remarkable Story of Risk*.

Bernstein's account begins in the dark days when people believed they had no control over events and so turned to priests and oracles for clues to what larger powers held in store for them. It progresses quickly to a new interest in mathematics and measurement, spurred, in part, by the growth of trade. During the Renaissance, scientists, and mathematicians such as Girolamo Cardano mused about probability and concocted puzzles around games of chance. In 1494, a peripatetic Franciscan monk named Luca Pacioli proposed "the problem of points"—which asks how one should divide the stakes in an incomplete game. Some 150 years later, French mathematicians Blaise Pascal and Pierre de Fermat developed a way to determine the likelihood of each possible result of a simple game (*balla,* which had fascinated Pacioli). But it wasn't until the next century, when Swiss scholar Daniel Bernoulli took up the study of random events, that the scientific basis for risk management took shape.

In the nineteenth century, other scientific disciplines became fodder for the risk thinkers. Carl Friedrich Gauss brought his geodesic and astronomical research to bear on the bell curve of normal distribution. The insatiably curious Francis Galton came up with the concept of regression to the mean while studying generations of sweet peas. (He later applied the principle to people, observing that few of the sons—and fewer of the grandsons—of eminent men were themselves eminent.). But it wasn't until after World War I that risk gained a beachhead in economic analysis. In 1921, Frank Knight distinguished between *risk,* when the probability of an outcome is possible to calculate (or is knowable), and *uncertainty,* when the probability of an outcome is not possible to determine (or is unknowable)—an argument that rendered insurance attractive and entrepreneurship, in Knight's words, "tragic." Some two decades later, John von Neumann and Oskar Morgenstern laid out the fundamentals of game theory, which deals in situations where people's decisions are influenced by the unknowable decisions of "live variables" (aka other people).

Today, of course, corporations try to know as much as is humanly and technologically possible, deploying such modern techniques as derivatives, scenario planning, business forecasting, and real options. But at a time when chaos so often triumphs over control, even centuries' worth of mathematical discoveries can do only so much.

In the fifth century BC, Athens became the first (albeit limited) democracy. In the seventeenth century, the Quakers developed a decision-making process that remains a paragon of efficiency, openness, and respect. Starting in 1945, the United Nations sought enduring peace through the actions of free peoples working together.

There is nobility in the notion of people pooling their wisdom and muzzling their egos to make decisions that are acceptable and fair to all. During the last century, psychologists, sociologists, anthropologists, and even biologists eagerly unlocked the secrets of effective cooperation within groups. Later, the popularity of high-performance teams, coupled with new collaborative technologies that made it "virtually" impossible for any man to be an island, fostered the collective ideal.

The scientific study of groups began, roughly, in 1890, as part of the burgeoning field of social psychology. In 1918, Mary Parker Follett made a passionate case for the value of conflict in achieving integrated solutions in *The New State: Group Organization—The Solution of Popular Government*. A breakthrough in understanding group dynamics occurred just after World War II, sparked—oddly enough—by the U.S. government's wartime campaign to promote the consumption of organ meat. Enlisted to help, psychologist Kurt Lewin discovered that people were more likely to change their eating habits if they thrashed the subject out with others than if they simply listened to lectures about diet. His influential "field theory" posited that actions are determined, in part, by social context and that even group members with very different perspectives will act together to achieve a common goal.

Over the next decades, knowledge about group dynamics and the care and feeding of teams evolved rapidly. Victor Vroom and Philip Yetton established the circumstances under which group decision making is appropriate. R. Meredith Belbin defined the components required for successful teams. Howard Raiffa explained how groups exploit "external help" in the form of mediators and facilitators. And Peter Drucker suggested that the most important decision may not be made by the team itself but rather by management about what kind of team to use.

Meanwhile, research and events collaborated to expose collective decision making's dark underbelly. Poor group decisions—of the sort made by boards, product development groups, management teams—are often attributed to the failure to mix things up and question assumptions. Consensus is good, unless it is achieved too easily, in which case it becomes suspect. Irving Janis coined the term "groupthink" in 1972 to describe "a mode of thinking that people engage in when they are deeply involved in a cohesive in-group, when the members' strivings for unanimity override their motivation to realistically appraise alternative courses of action." In his memoir, *A Thousand Days*, former Kennedy aide Arthur Schlesinger reproached himself for not objecting during the planning for the Bay of Pigs invasion: "I can only explain my failure to do more than raise a few timid questions by reporting that one's impulse to blow the whistle on this nonsense was simply undone by the circumstances of the discussion."

1.2 Decision Making - Meaning and Important Concepts

Every organization needs to make decisions at one point or other as part of managerial process. Decisions are made in the best interest of the organization. For that matter, decisions made by the organization are to lighten the way forward. Be it strategic, business activities or HR matters, processes of making decisions is complex, involves professionals of different genre. While small organization involves all levels of managers, complex organizations largely depend on a team of professionals specially trained to make all sorts of decisions. But remember, such a body alone cannot come out with final decisions. Here, the point is, decision making process is cumulative and consultative process. The process, overall, bears its pros and cons and would by and large emanate results and consequences in the organizations' overall growth and prospects. Decisions are taken to support organizational growth. The whole fabric of management, its day-to-day operation is rightly built on managerial decisions.

Discussions and consultations are two main tools that support and eventually bring out decisions. For instance, to take a decision on how to embark on new business activity suggested by strategic management team must have developed through series of consultative process, which is now available with implementation team. Here we see the cumulative effect of decision taken at one point by a different body of affairs. Decision taken by strategic managers is to push new and innovative business line or initiative. At this point the decision taken by such team becomes consultative point for discussion for implementation professionals. There is lot to debate, research and finalize. Is the new proposal viable? Is it innovative enough? Can there be growth stimulant in the strategies proposed? Handle-full of such questions evolved from the decision taken by strategic group has reflective influence on the next level of managerial consultations and meetings. Let us accept, at this point of discussion, that proposals submitted by business development team would largely depend on another set of deliberations in the board room.

Thus, the final decision to roll out a product or service is through cumulative interim decisions taken by various internal and external parties. And also, the final decision is reflective and founded on research and consultations. Whole process is a chain affair where one decision taken at one point and at one level shall have far reaching implications in the way an organization moves forward.

As a matter of fact, capable of taking critical decisions is one of the many attributes that every manager should have, be it top level or middle or entry level. By nature, a human being during his existence and by virtue of his instinct makes decisions for his survival, as social psychologists put it. By and large, managers are polished individuals to take decisions to affect others, ie the organization’s existence and growth thus is annotative with human endeavor to live and succeed. Success succeeds on the decisions taken, be it by an individual or an organization.

1.3 Steps of Decision-Making Process

Following are the important steps of the decision-making process. Each step may be supported by different tools and techniques.

1.3.1 Step 1: Identification of the purpose of the decision

In this step, the problem is thoroughly analysed. There are a couple of questions one should ask when it comes to identifying the purpose of the decision.

- What exactly is the problem?
- Why the problem should be solved?
- Who are the affected parties of the problem?
- Does the problem have a deadline or a specific time-line?

1.3.2 Step 2: Information gathering

A problem of an organization will have many stakeholders. In addition, there can be dozens of factors involved and affected by the problem.

In the process of solving the problem, you will have to gather as much as information related to the factors and stakeholders involved in the problem. For the process of information gathering, tools such as 'Check Sheets' can be effectively used.

1.3.3 Step 3: Principles for judging the alternatives

In this step, the baseline criteria for judging the alternatives should be set up. When it comes to defining the criteria, organizational goals as well as the corporate culture should be taken into consideration.

As an example, profit is one of the main concerns in every decision making process. Companies usually do not make decisions that reduce profits, unless it is an exceptional case. Likewise, baseline principles should be identified related to the problem in hand.

1.3.4 Step 4: Brainstorm and analyse the different choices

For this step, brainstorming to list down all the ideas is the best option. Before the idea generation step, it is vital to understand the causes of the problem and prioritization of causes.

For this, you can make use of Cause-and-Effect diagrams and Pareto Chart tool. Cause-and-Effect diagram helps you to identify all possible causes of the problem and Pareto chart helps you to prioritize and identify the causes with highest effect.

Then, you can move on generating all possible solutions (alternatives) for the problem in hand.

1.3.5 Step 5: Evaluation of alternatives

Use your judgement principles and decision-making criteria to evaluate each alternative. In this step, experience and effectiveness of the judgement principles come into play. You need to compare each alternative for their positives and negatives.

1.3.6 Step 6: Select the best alternative

Once you go through from Step 1 to Step 5, this step is easy. In addition, the selection of the best alternative is an informed decision since you have already followed a methodology to derive and select the best alternative.

1.3.7 Step 7: Execute the decision

Convert your decision into a plan or a sequence of activities. Execute your plan by yourself or with the help of subordinates.

1.3.8 Step 8: Evaluate the results

Evaluate the outcome of your decision. See whether there is anything you should learn and then correct in future decision making. This is one of the best practices that will improve your decision-making skills.

1.3.9 Curious Observation - First Step-in Decision-Making Process

Curious observation is the first step in the decision-making process. These two words, the curiosity and observation are very important for a decision-making process. Curiosity means the desire to know or learn about something. A person who is curious does not accept anything easily. He always has skepticism towards everything. The curious people always ask questions and try to search the answers for their questions. Being curious can help you in taking proper decisions.

You may ask this question that, how curiosity helps in decision making process? The answer is, when you are curious you can identify the situations in which decisions has to be made on the spot or in the future. The curiosity also stimulates other processes that help you in decision making. These include questioning, inquiring about things, experimentation, visualization, skepticism, evaluation, identification of different patterns, imaginative thought, logical reasoning, prediction, inference etc. All these processes will lead you towards appropriate decisions.

Curiosity not only helps you in decision making but it will also improve your other skills and abilities. If you are not a curious person then you can arouse your curiosity by reading newspapers, magazines, books etc. indulge yourself in discussions with family and friends, attend different exhibitions and conventions, observe the things going on around you and try to make a habit of questioning about everything and not accepting each and every thing as a fact.

The other word is observation which means the ability to notice significant details or the process of observing different things in order to gather information. If you are observant then you can become a good decision maker. It helps you to identify every significant detail regarding your problem and its solution. It is important that you closely observe everything related to your problem. Note down each and every details that you have gathered through your observation. For example if you are running a company and you have to take decision that, from which supplier you will buy your products, then the first thing that will help you in decision making is through observation of the sample products. Through observation you can analyze the quality of product and then by following the further steps of decision making you can take a better decision for your company.

So through these two things: curiosity and observation i.e. curious observation you can make your decision process easy and also effective. During the decision making process, don't stop your thinking process and think over the problem again and again. Set your thought free and try to improve your thinking skills. Imagine and visualize the whole scenario in your mind so that you can predict the outcome of your decision. Curiosity during the decision making process will lead you to dissatisfaction and dissatisfaction will lead towards improvement in your decision making abilities. This first step of curious observation is very important step and a good decision maker always follows this step. Implement this step in your decision-making process and get good outcomes.

1.3.10 Individual Decision-Making Pros and Cons

Individuals tend to think and question before performing. This is fruitful in analysis and forecasting of individual's behaviour. Individual decision making has certain pros and cons, few of which are mentioned below:

a. Pros of Individual Decision Making

- An individual generally makes prompt decisions. While a group is dominated by various people, making decision-making very time consuming. Moreover, assembling group members consumes lot of time.
- Individuals do not escape responsibilities. They are accountable for their acts and performance. While in a group it is not easy to hold any one person accountable for a wrong decision.
- Individual decision-making saves time, money and energy as individuals make prompt and logical decisions generally. While group decision making involves lot of time, money and energy.
- Individual decisions are more focused and rational as compared to group.

b. Cons of Individual Decision Making

- A group has potential of collecting more and full information compared to an individual while making decisions.
- An individual while making any decision uses his own intuition and views. While a group has many members, so many views and many approaches and hence better decision making.
- A group discovers hidden talent and core competency of employees of an organization.
- An individual will not take into consideration every members interest. While a group will take into account interest of all members of an organization.

Section 2: Decision-making in the organization

2.1 Organizational Decision making

Decision-making is a core activity of organizational life. Poor or bad decisions have huge consequences for organizations, many times even threatening their existence. However, it was not until Simon (1957) wrote his book Administrative Behavior that decision making was introduced as a focal point for studying organizations. Since then, the study of decision making has become an important research topic in organizational theory and has made many contributions, contributing to some extent to the status that organizational theory enjoys today (Hodgkinson and Starbuck 2008).

In the decision-making literature, decisions have been classified according to decision types. A distinction is made between structured and unstructured decisions or, as introduced by Simon (1977), between programmed and non-programmed decisions. Simon (1977) stated that “decisions are programmed to the extent that they are repetitive and routine, to the extent that a definite procedure has been worked out for handling them so that they don’t have to be treated from scratch each time they occur” On the other hand, decisions are non-programmed “to the extent that they are novel, unstructured and unusually consequential”. Programmed or structured decisions involve well-defined, measurable and compatible criteria, while non-programmed or unstructured decisions come under the heading of “problem solving” (Simon 1977). Operational decisions tend to be structured, while strategic decisions tend to be unstructured (Simon 1977). In particular, Mintzberg et al. (1976) define as strategic those decisions that are “important in terms of actions taken, the resources committed, or the precedents set” and which are usually made under uncertainty and do not have programmed solutions. According to the rational choice theory, organizational choice, which is seen as an extension of individual choice, operates by selecting the alternative with the highest expected value once specific goals have been defined, all the alternatives of achieving the goals have been identified, and their consequences have been evaluated. However, critics of these rational theories have highlighted a number of limitations of this view of decision-making and the use of information. In particular, studies have shown that making strategic organizational decisions is, in reality, far from what the classical decision theory prescribes

(Simon 1957) as will be elaborated later. A further limitation to the rational approach to decision making is that people don't necessarily take a rational approach to making decisions. Organizational theorists have also documented other approaches to decision making, such as judgement, intuition and negotiations (Bazerman and Moore 2008), which are used by decision-makers instead of the rational approach. These other models of decision-making rely on experience, beliefs, and unconscious automatic processing of a situation for making decisions. Proponents of these models have remarked that decision-makers do not use entirely rational information processes.

Simon (1957) was the first to point out that decision makers do not necessarily act rationally (according to formal theories of choice) in practice. He noted that rationality is an ideal state that cannot be reached by human beings: The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world - or even for a reasonable approximation to such objective rationality. (Simon 1977, p.198) In reality what exists is "bounded rationality": humans can only be rational to a certain extent. This is because it is not always possible to define goals, and it is impossible to consider all possible alternatives and to evaluate all possible consequences. In addition, there are costs associated with collecting, analyzing and interpreting information. The complexity of reality exceeds the human capacity to process information. According to Simon (1977) the consequences of the bounded rationality are larger than one might initially think: It is only because individual human beings are limited in knowledge, foresight, skill, and time that organizations are useful instruments for the achievement of human purpose; and it is only because organized groups of human beings are limited in ability to agree on goals, to communicate, and to cooperate that organizing becomes for them a 'problem'. The prominent work of Simon, which emphasized the role of information processing and decision making served as a driving force for further research on organizational decision making and behavioral decision theory. Numerous researchers from different fields have proposed models of decision-making in the light of bounded rationality and limited information (Simon 1957). However, focuses entirely on organizational decision-making, looking at organizations as information processing systems. Firms are coalitions of participants and decision-makers with conflicting interests who use standard rules and procedures to avoid uncertainty and ambiguity in decision-making. Today, the above description of the firm, the notion of bounded rationality and limited information are widely acknowledged by the proponents of rational theories. Other organizational scholars conducted research on topics related to decision-making and provided new insights from perspectives outside the traditional information processing standpoint. The conceptualization of organizations as coalitions of participants with conflicting interests spurred a series of studies looking at decision-making from a political perspective, for instance. This body of work emphasizes how different stakeholders and organizational groups influence and compete for scarce resources. Since different organizational groups have different goals, conflict and disagreement arise. The competition for scarce resources and the pursuit of different goals make the organizational decision making process inherently political . In relation to the concept of bounded rationality, Miller (2014) observed that: In Simon’s definition of the term, “bounded rationality” is largely the result of human and organizational constraints. Arguably, this view underplays the role of power and political behavior in setting those constraints. Many writers have pointed out that decision-making may be seen more accurately as a game of power in which competing interest groups vie with each other for the control of resources. Pfeffer (1981), with his book Power in Organizations, provided an extensive analysis of power in organizational settings and positioned his political model against other decision-making models. As such, information processing and not decision-making becomes the principle of organization and organizations can be understood not in terms of decision-processes but rather in terms of information processing and, more specifically, their means for reducing ambiguity. Weick (1969) summarizes his organizing model as follows: The central argument is that any organization is the way it runs through the processes of organizing... This means that we must define organization in terms of organizing. Organizing consists of the resolving of equivocality in an enacted environment by means of interlocked behaviors embedded in conditionally related processes organizing is directed toward information processing in general, and more specifically, toward removing equivocality from informational inputs. Refining the above ideas, (Weick1969) later introduced the view of organizations as interpretive systems: Organizations must make interpretations. Managers literally must wade into the swarm of events that constitute and surround the organization and actively try to impose some order on them... Interpretation is the process of translating these events, of developing models for understanding, of bringing out meaning, and of assembling conceptual schemes. According to this view decision-makers process information, interpret it, and enact their environment. Central to this view are the ‘assembly rules’ that govern information processing and the means for reducing ambiguity, which together define the interpretation process. Assembly rules consist of the procedures or guides used by organizations to process information into a collective interpretation. A collective or common interpretation of the external environment is achieved by the efforts of decision-makers to reduce equivocality by extensively discussing ambiguous information cues (Weick 1969). Another nascent theme in organizational decision-making is the concept of intuition and its role in managerial and organizational cognition as another mode of making decisions. Intuition is an automatic processing mode that is beyond conscious control and that enables decision-makers to process vast quantities of information rapidly without being conscious of this process happening (Hodgkinson and Starbuck 2008). Intuition "depends on the use of experience to recognize key patterns that indicate the dynamics of the situation" . This model of making decisions differs from the rational model in the sense that decision makers do not consider all the alternatives but rather match or recognize patterns or unconsciously collect cues that show them the right alternative almost immediately without any effort. However, as noted by Klein (1998), contrary to the rational model, decision-makers have trouble explaining and defending their intuitive judgments to others. In parallel with the developments in organizational decision-making, significant research developments were achieved within the behavioral decision theory. Behavioral decision theory has its roots in the psychology of choice behavior. Kahneman and Tversky made their mark in the study of judgment under uncertainty, the development of the heuristics and biases paradigm (Kahneman et al. 1984), as well as the development of prospect theory and framing in individual choice behavior (Kahneman and Tversky 1979, 1984). There are several characteristic of organizational decision making that distinguish organizational choice from individual choice behavior. Ambiguity is one of the most important concepts in organizational decision-making (March 1994). It refers to the ambiguity of the information available, the ambiguity of preferences and consequences, and the ambiguity surrounding interpreting and evaluating past decisions. In contrast, in lab experiments such as those employed by behavioral researchers there is no information, preference or interpretive ambiguity (Hodgkinson and Starbuck 2008;). Further, organizational decisions are made in ongoing processes of decision-making. In organizations, decisions are interrelated and sequential in nature and in such processes commitment rather than judgmental accuracy might be required. Other characteristics of organizations that affect decision making in organizational settings include the effects of positive and negative incentive systems that are in place or the lack of them and rule following instead of processing available information when making repeated decisions (March 1994). Finally, conflict, always present in organizations, has a large impact on the making of organizational decisions. These characteristics of organizational decision-making pose further limitations to rationality as an appropriate model to describe how decisions are made or happen in organizations. Rationality manifests itself in formal analysis such as information gathering, processing and use. In this sense, BI as a process of gathering and analyzing data represents a rational process and the BI output as the outcome of data-driven analysis represents the output of formal analysis. However, as described above, decision-making is not always a rational process and, as a consequence, formal analysis is not always used as intended by the rational approach, i.e. to reduce uncertainty in decision-making. In the following subsections, three complementary research streams on the role of formal analysis in organizational decision-making are presented.

Use of formal analysis in organizational decision making. The majority of normative academic research has always advocated for more systematic and formal analysis of problems, information and environments when making decisions. However, empirical studies of decision-making in organizations continuously show that although more formal analysis is being used in organizations, their decision-making processes have not substantially changed (Baker et al. 2004). Simon (1977) predicted that with the increasing sophistication of formal analysis techniques and the availability of information the classic rational model would provide a progressively more accurate description of how decisions are made in organizations. Yet, as Backer et al. (2004) point out, this is not the case. In the next subsections, studies on the use of formal analysis within organizations are presented. This research suggests that in practice the use of formal analysis for informational purposes is only one of many purposes for which it is used in organizational settings. Rather, formal analysis is also used to communicate and interact with others, influence decision-makers and justify decisions and actions. Below, I adopt the categorization provided by Backer et al. (2004) to present the different yet complementary streams of research on the use of formal analysis in organizational decision-making.

The functional list view–Managing uncertainty The functionalist view adopts a rational and bounded rationality approach, regarding information as being used to inform decision-makers and hence to reduce uncertainty. This school of thought views decisions as rational processes composed of linear phases with specific beginnings and ends which is evident in the work of Simon (1957) and Mintzberg et al. (1976). For example Simon (1957) describes three phases of organizational decisions processes: the intelligence phase, the design phase and the choice phase. Following in the same footsteps, Mintzberg et al. (1976) also identify three phases, called identification, development and selection, which were further broken down into seven routines: recognition, diagnosis, search, design, screening, evaluation and authorization. The studies found that although information was collected and organized in the different phases it was not always used as theory prescribes – that is, to determine decisions. Thompson's (1967) contingency model proposes that decision-making based on formal analysis or "calculation" is only possible when there is no uncertainty about the goals and the means to achieve them. That is, when the preferences concerning the outcomes and the beliefs about causeeffect relations are clear, it is possible to collect unambiguous information about alternatives and to perform the analysis according to the specific criteria required. When these two contingencies are not clear, Thompson (1967) suggests the use of other approaches in decision-making rather than formal analysis. In particular, when goals are clear but the means are not then the use of majority judgment is recommended as being more appropriate. Conversely, when the goals are ambiguous but the means are clear then Thompson suggests the use of bargaining in order to achieve a compromise on the goals. When both goals and means are unclear a problematic situation is created which is called "anomie". This situation according to the authors calls for the use of the "inspiration" or intuition of a charismatic leader.

This contingency model was tested in an empirical study by Nutt (2002) in which data about 376 strategic decisions were gathered and analyzed. The study confirmed Thompson's model as a sound prescriptive guide that could predict successful decisions according to the fit of the decision context with the process followed. However, Nutt's study also revealed that decision-makers did not always follow the prescriptions of Thompson's model. Specifically, Nutt criticized the fact that decisionmakers were prone to using the wrong decision approach, leading to wrong decisions such as adopting rational procedures when negotiations or judgment would have been more appropriate according to the model (Nutt 2002). Researchers of cognitive psychology investigating decision-making and negotiation underline the importance of data in the decision process in order to avoid cognitive biases (Bazerman and Moore 2008). These models assume that managers, who are bounded rationally but are participating in situations marked by uncertainty and complexity, use heuristics or rules of thumb when making decisions (Bazerman and Moore 2008). However, sometimes heuristics lead to systematic errors or cognitive biases and thus to sub-optimal decisions (Bazerman and

Moore 2008). The cognitive limitations and biases of individuals when processing information.

Overall, this literature suggests that decision-makers apply heuristics (or shortcuts) that simplify decision making (Kahneman et al. 1979) in an attempt to avoid the cognitive burden of using analytical mental procedures. The application of heuristics in decision-making might be an explanation for the discrepancies found by Nutt (2002) between the actual behavior of decision-makers and the prescriptions of Thompson's (1967) contingency model. In order to improve decision-making, researchers in this field have proposed methods of acquiring more information in order to reduce bias. Nutt (2002) noted that in the majority of decisions some kind of information is present. This stream of research is influenced by researchers who have a normative view of the individual as being essentially rational (Bazerman and Moore, 2008). According to this view, formal analysis is a positive and useful feature of decision-making that leads to better decisions. Above, the functional view of the use of formal analysis was presented. According to this view, formal analysis is used in decision-making to decrease uncertainty and to avoid producing biases from the use of heuristics. Several limitations of the functional view in achieving optimal decisions and avoiding systematic errors were also presented. Nonetheless, This 'information processor' view of individuals ignores the social context in which decision-making occurs The next stream focuses exactly on the social context and specifically the sociopolitical processes that take place around and within decision-making processes.

The political view–Managing equivocality Empirical studies of organizational decision-making have reported that formal analysis is used not only to inform decisions but also for political reasons not encompassed by the rational approach. In this regard, the organizational decision-making literature has documented many studies in which formal analysis is used to support already made choices, to advocate for a specific coalition over another (or to call attention to or deflect attention from specific issues (Bazerman and Moore 2008) showed that when decision makers were accountable to others, the extent of their engagement in information search and analysis changes according to their views. If the views of superiors are known then people tend to search for information that will be acceptable to their superiors and to analyze it accordingly.

When the superiors' views are not known, it showed that people tend to increase search and analysis in terms of depth but also breadth of alternatives considered, in order to be prepared for any possible disagreement that might arise with their supervisors. As such, the formal analysis and socio-political processes are interdependent. Nutt (2002) goes a step further, based on an empirical study of formal analysis in organizations, and argues that formal analysis and socio-political processes are in fact symbiotic. Specifically, she remarks that: Formal analysis would be less necessary if everybody could execute their decisions themselves, and nobody had to convince anybody of anything. In fact, one could hypothesize that the more decision-making power is shared between people who do not quite trust one another, the more formal analysis will be important. March (1979) argues that because of this continuous misrepresentation or political use of information in organizations much information and analysis is disregarded, overlooked or cautiously used. As a result there is an adaptation process in which decision makers learn to be skeptical of overly clever or strategic people and strategic people correspondingly learn not to be overly smart in their information manipulation activities (March 1979). Pointing to the importance of understanding the social processes involved in decision making delve into the socio-political nature of organizations to show that the answer to better decision-making does not necessarily lie with the provision of greater quantities of “more accurate,” “objective” and timely data, but rather requires an understanding of the social processes of negotiation involved in deciding. The fact that most research on decision-making has focused on information processing and less attention has been paid to understand how decision-makers socially construct their organizational worlds and their external environment. In their article, the authors draw on sociological insights to integrate the computational and interpretive perspectives on organizational cognition to provide a more complete account of organizational decision-making processes.

They particularly emphasize the aligning of interpretation and influencing processes that organizational members engage in through the use of symbols, rituals and language to shape cognitions and preferences. All these studies have demonstrated that the generation, analysis and presentation of information in organizations is not at all innocent. Formal analysis can be and is used as an instrument of power and persuasion, which in turn can lead to information misrepresentation (Feldman and March 1981). Formal analysis arises from social construction because data and information are attributed to entities by people. According to Griffith et al. (2008) even if technologies are used to perform the analysis, these technologies reflect the limitations of their designers. Searches for information and uses of it depend on how designers characterize and classify information.), managers use symbols in order to shape organizational cognition and preferences. One such symbol is formal analysis itself.

The symbolic view–Managing irrationality Contrary to the rational approach, there is also evidence that data and information are used in obscure, irrational ways. For example Feldman and March (1981) observe that organizations gather and use information that has remote relevance, that information is used to justify already made decisions, that requested information is not considered and that more information is requested while already available information is ignored. This use of information goes against the classic theory of rational choice which suggests that information and its dimensions of relevance, reliability and precision will be pursued only to the degree that the cost does not exceed the value of the information (Feldman and March 1981). Why would organizations gather information that has no relevance to decisions? That is a waste of organizational resources. A plausible explanation for such a behavior is provided by Feldman and March (1981) who draw on the symbolic value of rationality and formal analysis in western societies. The concept of "intelligent choice" appears to have had a great impact on people's expectations of how choices should be made while at the same time it has not had the same impact on their actual behavior (Feldman and March 1981).

Especially in organizational settings, the concept seems to have become institutionalized – decision making practices have to convey rationality but do not necessarily need to have a rational outcome. Because it is so important to exhibit rationality in decision-making processes (Weber 1947) and because the systematic use of formal analysis is directly correlated to rational behavior, its symbolic value can become even more important than its informative value at times (Feldman and March 1981). This is because rationality is seen as the ideal way to make decisions. As a result, formal analysis is seen as a positive and useful characteristic of decision-making processes, while the socio-political elements are seen as counter productive. In this way, formal analysis is viewed as an objective method for taking politics out of decisions. The attribution of a decision to formal analysis allows the decision-makers to distance themselves from politics, which are seen as negative (Power 2004, 2003).

In this sense, information analysis and use is considered as a legitimate way to make decisions and a decision maker who gathers and analyzes information is considered competent and inspires confidence, even when the information might not be directly relevant or helpful. Indeed, the very assignment of a decision to formal analysis is a political act of legitimization (Pfeffer 1981). As such, decision makers often use formal analysis because it helps them to convey an appearance of rationality to other organizational members or society at large, which by itself provides legitimacy to the chosen course of action. This use of formal analysis is not so much political as it is symbolic. Formal analysis in these circumstances provides the decision-makers with a sense of rationality which in turn creates for them the necessary trust and confidence to act. When the dominant norm is rationality, there is increased adoption and ritualized use of managerial techniques and information (Lozeau et al. 2002). However, as Feldman and March (1981) argue that symbols and norms are not static but rather dynamic. As such while the inquiry, collection and use of information might be originally driven by its symbolic value eventually, the same information might be proved to be useful in ways that were not initially predicted. Further research on the use of formal analysis shows that even when it is used as a symbol or to influence and direct the attention of others, it provides a basis for decision makers and creates a collective situated space in which decision-makers can discuss their interests and preferences for particular decisions. Blackler (1993) portrays formal analysis as an interactive process that includes at the term each day by using a tool like Google's BigQuery. This is a free service that e same time symbolic, political and social elements. It is through this interactive process that decision-makers attempt to establish a common ground among them by making their assumptions explicit.

2.2 The Process of Corporate Decision Making

Corporate decision making happens at various levels in organizations and can be top down or bottom up. The difference between these two styles of decision making is that the top-down decision making is done at the higher levels of the hierarchy and the decisions are passed down the corporate ladder to be implemented. On the other hand, bottom-up decision making is done by giving autonomy to the middle managers and the line managers to take decisions based on the conditions and circumstances existing in their teams. In many organizations, what we see is a top-down decision making in the realms of policy, strategic focus, direction in which the organization has to proceed and bottom-up decision making about the day to day running of the teams.

It needs to be remembered that the middle management is often called the "sandwich" layer because they have to implement the decisions made above and at the same time have to decide about how to run the teams and have to communicate them to the lower levels as well.

The point here is that in any process of corporate decision making, the actual implementers play a critical role since the best laid plans of the top management can go awry in case there is no commitment from the middle management. Hence, many organizations organize off site meetings at resorts and other places where the senior management briefs the middle management about the decisions that they have taken and how it would impact the organization.

Corporate decision making is also characterized by consensus or the lack of it. Like in the real world, corporations often have power centers and groups that have their own agendas and hence arriving at a consensus can be cumbersome for the CEO or the Chairman of the Board of Directors. It is because of this reason that many corporations witness periodic restructurings with regards to organizational structure and with regards to turnover among the top management. In recent months, Infosys has seen rapid and often turbulent situations in the company because of the power struggles at the top as well as lack of consensus among the top management about the direction that the company ought to take.

The other aspect related to corporate decision making is that many organizations thrive on leaders who have a "halo" around them and hence decision making is smooth because the rival power centers often concede to the leader's charisma or his or her ability and vision. Again, Infosys has seen this happen when with the retirement of its legendary founder, N R Narayana Murthy; the company is going through a bad phase with competing factions jostling for control. Abroad, Apple is an example of a company that relied on the halo effect of its founder, Steve Jobs and once he passed away, there is some uncertainty about the way the company should take in the market.

In conclusion, corporate decision making is successful as long as there is a "glue" to bind the organization together in the form of charismatic leaders or an organizational culture that values coherence and imposes stability. Once any of these conditions are removed, then the organizations fall into a self-defeating trap wherein the process of corporate decision making is impaired leading to the loss of competitiveness of the company.

2.3 The OODA Loop and Decision Making

An important concept in the field of decision making is the OODA Loop or the Observe-Orient-Decide-Act loop. This refers to the strategic advantage that a decision maker gets over his or her opponent when he or she observes the situation and orients themselves and then decides and acts accordingly. This concept was introduced primarily in combat and strategic warfare where it was believed that a combatant's "edge" over his or her opponent happens when the OODA loop is fully functional. The term and the concept were proposed by the military strategist and member of the United States Air Force, Colonel John Boyd. The theory underlying the OODA loop is that decision making within our minds happens according to the way in which the recurring loops of observation, orientation, decision, and action happen in response to a situation. The basic premise is that decision makers must be agile and alert to the situations and have a clear head and cool mind to take a decision lucidly and cogently.

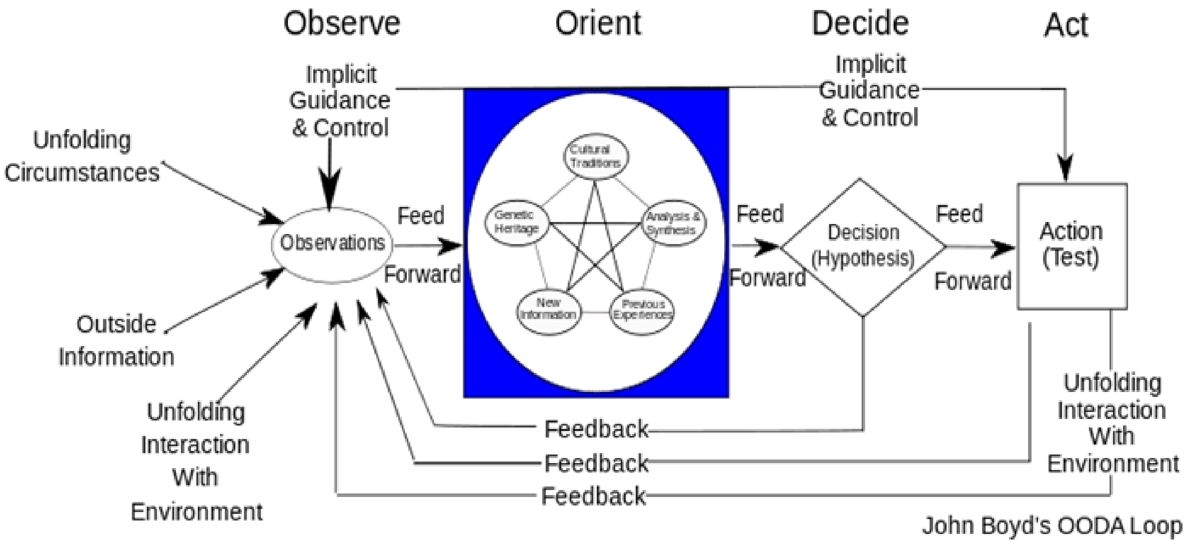


Figure 22.John Boyd's OODA Loop (Juneja, 2019).

Figure 22 depicts how the OODA loop works in real life situations. The inputs from the environment are taken by means of information, interaction with the environment and the circumstances that unfold with the interaction. Then the orientation to the situation happens by means of the individual's internal processes and the perceived expectations along with his or her own conditioning. Then the next stage where the decision has to be taken takes over where the information from the situation meets the individual's thought processes leading to decision making capabilities. Finally, the decision leads to the action where the decision is actualized and made operational. The important thing to remember about the OODA loop is that feedback is an integral component of all stages with information flowing back and forth between the individual and the situation (Juneja, 2019).

It is worth nothing that the OODA loop calls for exemplary mental and physical fitness. The need for this fitness is that the decision maker ought to seize the situation and then comprehend the same along with an ability to take quick decisions on the spot depending on the way the situation unfolds. Though the concept was introduced in the Armed forces, this is being regularly applied in the corporate world as well. The reason being that the OODA loop and the concept of decision making that it implies is a sound idea and something that can be used to improve the decision-making process (Juneja, 2019).

In the hectic corporate world, there is often no time to lose especially when quick decisions have to be taken and hence the OODA loop provides a good basis to the decision making and the way in which the decision makers can go about their decision-making process (Juneja, 2019).

The first and the important thing to remember about the OODA loop is that it is mainly concerned about situations that involve split second decision making. Considering the fact that it was developed by an Air Force pilot, it is natural that the OODA loop describes decision making in situations that are combat oriented in nature. However, this does not preclude its use in corporate decision making as there are many situations in which the decision makers have to take split second decisions with little or skewed information. For instance, during board meetings and meetings of shareholders, important decisions and announcements have to be made depending on the exigencies of the situation (Juneja, 2019).

For the sake of illustration and during hostile board meetings or meetings of senior management where the decision makers have to confront other managers with competing agendas, they have to react quickly and agilely to ensure that the decision that they take is in the best interests of the organization and its shareholders (Juneja, 2019).

The time between receiving the information and taking a decision is often in the seconds and minutes and hence decision makers have to react quickly to the demands of the situation. Often, this means that decisions have to be made by getting inside the minds of the opponents. For instance, getting to know what the opponents' strategies are and their intentions by assessing their body language and their words would be invaluable to the decision makers (Juneja, 2019).

Further, the noteworthy aspect is that the decision makers have to rely on gut feelings and emotional intelligence to arrive at the decision. This means that the decision makers have to trust themselves and their judgment to take the decision that would be in the interests of the organization and its shareholders. This often involves acting with imprecise or skewed information. The reason for this is that the opponents' themselves would be actualizing their OODA Loops and hence it becomes a combat situation where the one with the better decision-making abilities wins. This is the reason for the popularity of the OODA loop in contemporary organizations where training and mentoring often involves familiarizing with the OODA loop (Juneja, 2019).

2.4 Decision Making in Self Directed Teams

It is often the practice to give autonomy to many teams and let them take the decisions that affect their day-to-day affairs as well as some strategic issues. These are the so-called self-directed teams that exist in all organizations where the managers of these teams take the decisions regarding the management of the team with greater autonomy than the other teams. These self-directed teams are liked by many managers since there is greater freedom and greater say over their affairs and the rank-and-file employees also like these teams because it gives them greater control over their work. However, senior management in most cases does not like to cede autonomy and hence there is often a tussle going on between senior management and middle management as far as these self-directed teams and their functioning goes.

The standard defense that the senior managers in these divisions and regions offer is that the passing down of the autonomy to the rank and file might not be practically possible given the lack of strategic focus and direction that individual teams have which makes them take orders instead of deciding for themselves.

Of course, the intra-organizational tussles that go on between the senior management and the rank-and-file employees along with the middle managers might make for interesting gossip but in reality these tussles have negative effects on the organizational fabric. Hence, a possible solution to this issue would be to ensure that sufficient autonomy is ceded to the middle managers without compromising on the strategic imperatives. This can be done if the decision making is decentralized in some functions like HR, Admin, Finance, Operations and Project Management and Project Delivery and at the same time retain control over the overall strategic direction and focus that the company must take.

Though this solution might sound simplistic, in reality this is something that has been actualized in many organizations especially in Fidelity and Unilever where functional and divisional heads as well as regional heads take decisions regarding these activities without interference from the higher ups. Though there are bound to be some issues that crop up from time to time because of this arrangement, there are some positive benefits to this arrangement. These benefits are to do with the way in which the regional and divisional autonomy manifests in better decisions made about the day to day operations based on local conditions instead of centralized decision making that is top down and done without knowledge of ground realities.

In conclusion, decision making in self-directed teams must be encouraged without ceding complete control over the larger areas of policy and strategy. This can be actualized with some deft planning of the organizational structure and reorienting the organizational culture (Juneja, 2019).

2.5 Top-Down Decision Making and Bottom-Up Decision Making

We consider whether top-down decision or bottom-up decision making is effective. To consider this comparison it would be useful to think of top-down decision making as being akin to someone sitting on top of a tree telling those at the bottom about how best to take care of the garden on the ground. On the other hand, bottom-up decision making is akin to those at the bottom deciding on how best to tend the garden and ensuring that the other trees grow to the same height as well. It does not take a genius to figure out that those at the bottom have a better understanding of the ground realities than those at the top. The point here is that top-down decision making is becoming redundant in these days when autonomy and decentralization are the norm.

Having said that, it is important to realize that not all decisions can be made by those at the middle or lower levels of the corporate hierarchy; Indeed, it is the case that most decision making pertaining to organizational policies, firm wise strategy and customer acquisition and customer relationship management has to be done from the top since the view from the top is unhindered as well as the top management having the experience and the foresight to take such decisions.

The point that needs to be noted is that bottom-up decision making works well when the day to day running of the teams and divisions are concerned. It does not work well in cases of strategic acquisitions and firm wide policy making that is best left to the top management. Of course, which is better also depends on the type of organization since those in the services sector operate in more democratic ways as compared to the firms in the manufacturing sector. This is because of the very nature of the work which is different in these two cases. Since manufacturing is all about set routines and machines, the instructions have to be sent from the top since the decision making as well as the implementation operates in linear ways. However, the services sector is driven by complexity and non-linearity and hence, decision making has to be done according to the needs of the situation and the players involved in the decision-making process have to act in ways that maximize their benefits from the decision.

Finally, this is the bottom-line requirement for any decision-making process i.e. how much benefit that the decision brings to the firm as opposed to the costs incurred in such decision making. If the benefits far outweigh the costs, then decisions can be done in top down or bottom-up manner with outcomes that are favourable to the whole organization. There are many instances of decisions taken at the top that were not actualized and implemented properly because of incoherent communication and inconsistent transmission. On the other hand, there are many decisions that have been taken by the middle and lower levels that lack the experience and foresight not to mention the strategic depth which have resulted in short term thinking.

In conclusion, top down or bottom-up decision making is effective according to the needs of the situation and is determined by several factors (Juneja, 2019).

2.6 Decision Makers and the Zero-Sum Game

Decision making need not necessarily be a zero-sum game where one party benefits at the expense of the other. For instance, it is common in many organizations for decision makers to favor one group over the other which results in a situation where one group wins, and the other group loses. This is the zero-sum game hypotheses which indicate that decisions are taken to benefit one group over the other. There is an alternative to this situation and that happens when decision making is done in such a manner that produces synergies instead of losses to one group. The synergies that we are talking about result when decision making is carried out in such a way that the eventual decision considers the needs of all groups and produces a result that approximates the sum substance of each of the players' interests.

The real-life models for this can be seen in the way political parties and governmental organizations practice democratic decision making that satisfies to a large extent the aspirations and interests of all the players. This is done by creating resources to meet the demands of the various groups and investing them to the satisfaction of all the parties.

On the other hand, there are instances (especially in the international geopolitical context) where decision making often results in one nation losing out at the expense of another winning. However, even in the international scenario, such a situation can be avoided if the Ricardian principles of free trade are implemented. According to this, a nation that is good at making one particular product can export that and import some other product from another country which it cannot produce on its own.

Of course, decisions often are zero sum games and the point that we are making in this article is that decisions can be taken by finding a common ground where everybody is better off in the end. For instance, by making the parties forego some amount of resources that they would have got out of the outcome, decision makers can ensure a little bit of everything for everybody. The point here is that if we have to navigate the turbulent times of the 21st century, we need everyone to sit together and thrash out their differences and arrive at an understanding. This is the only way in which we are going to survive.

2.7 Conflict Resolution and Decision Making in an Uncertain World

Decision makers in contemporary organizations are confronted with uncertainty and ambiguity in their everyday lives. Not only do they have to contend with rapidly changing trends and fluid situations, the data they get from the ground or from market research becomes redundant with no time. This has given rise to confusion and chaos in the way organizations approach the future. This situation can be remedied by the use of scenario based decision-making where the managers draw up possible scenarios that the company might have to contend with in the short term, medium term, and longer term.

By drawing up scenarios that consist of simulations of the best-case situation and the worst-case situation, the managers would be better able to take the right decision when the situation manifests itself. The point here is that looking into the future is impossible except for oracles and clairvoyants. Hence, some sort of grip on the future must be firmed up by planning for all possibilities.

Over the last couple of years, global businesses had to contend with multiple economic shocks starting with the bankruptcy of the investment bank, Lehmann Brothers that nearly brought down the global financial system. Next, the Eurozone crisis erupted that threatened to bring entire governments to their knees. Now, we have the specter of diminishing resources and runaway inflation. In this context, it becomes important for managers to draw up scenarios that would happen with a certain degree of probability. For instance, it would be better for managers to think of the eventuality of Greece leaving the Eurozone and then planning for it accordingly. For managers in sectors that do not have exposure to financial instruments in a major way (after all, which sector is immune from financial shocks?), they can simulate models and scenarios where a war in the Middle East is predicted and then base their strategies accordingly.

The point here is that when there is so much uncertainty, it becomes tough to anticipate events. Hence, by drawing up scenarios that simulate the worst and the best as well, decisions can be taken that would derive advantage to the organizations. When one adds complexity to the uncertainty and ambiguity that pervades the current world, one is even more muddied and muddled to take decisions. For this, managing the present, it is a challenge and hence many organizations leave future forecasts to consultants and management experts. However, this need not be the case and in-house expertise can be developed to deal with emerging scenarios.

Any decisions taken at any level have to take into account the conflicting needs of the individuals who are affected by the decisions and hence conflict resolution is a part of the decision-making process. How well the conflicts are resolved depends on the skill and leadership traits of the decision maker.

After all, any decision that is taken is to balance competing interests and is essentially an allocation of shared resources among the different groups. The point here is that in any organization there are scarce resources that need to be allocated among competing groups and hence the decision maker has to ensure that all the needs and concerns of the different groups are taken into consideration when making the decision.

Since most decisions involve some emotional component as well, the decision makers have to be especially sensitive to the needs of the people who are affected by the decisions.

Consensual decision making ensures that most concerns of the different groups are heard and taken into account. However, in the real world organizations, decision making by consensus might not be feasible since each group has its own agendas. Hence the decision makers have to ensure that the decisions that they take involve some amount of consultation and some amount of overriding the individual agendas. The reason being that though individual concerns can be taken into account, the decision makers have to keep the interests of the organization in mind and hence proceed accordingly. This is needed so as to prevent individuals and groups hijacking the decision making process with their agendas.

In most organizations it is common for the decision makers to elicit as much information as possible from the individuals and then only take the decision so as to provide balance and grievance redressal to the affected parties.

As this article has discussed, conflicts are inevitable when decisions are taken and the best way to deal with conflicts is to resolve them to the satisfaction of the aggrieved parties. However, this is easier said than done in this competitive world where nobody is willing to lose out on lucrative resources and forego their chances. So it takes quite a bit of skill and managerial abilities not to mention leadership traits to ensure that the decisions result in amicable settlements among the competing groups. The point here is that while it is not possible to please everybody, it is possible to give them a fair hearing and be patient with them so as to give an impression of consensual decision making.

In extreme cases when the competing groups do not agree or abide with the decision, it is left to the higher-ups in the organization to play the role of peacemakers. This is the process of appeal to the senior management as part of the concerns and grievance redressal. This is an essential component of the decision making process in organizations and only when there is active recourse to appeal can true decision making work.

Section 3: Business Decision Making in 21st Century

We live in a world of increasing complexity and compression of time which means that the systems whether they are business structures, economic and political institutions, or even societal systems need to take into account complexity and increased interconnection along with reduced time to react and acceleration of life. For instance, imagine how your daily life would play out in terms of these aspects. You go to work for a firm that is most probably engaged with multiple stakeholders spread out all over the globe and with minute interactions between and with these stakeholders. This means that your business processes, IT (Information Technology) systems, and associated organizational structures have to be resilient to withstand the shocks and stresses as well as the pressures of integration, interconnection, globalization, complexity, acceleration of time, and compression of decision making windows. Therefore, business decision makers have indeed tough task on their hand as they grapple with the complexities and challenges of 21st century business landscapes.

3.1 Designing Failsafe Systems

Any design of a failsafe system must take into account the fact that the system is strongest or weakest as its weak link meaning that any disruption to the complex and intricate supply chain and value chain is subject to the resilience of each of the links and more importantly, the strength of the joints that tie in these links. Therefore, business decision makers have to first map out the strengths and weaknesses of each of the steps in the supply chain and each of the links in the value chain and then ensure that the threats are addressed in terms of strengthening each component and the entire system is geared to leverage the opportunities afforded by the integration of the world economy. In other words, just as businesses have benefited from the explosion of global trade and commerce, they have also been left vulnerable to the shocks and the shifts in the changing contours of the global economy.

A typical day for a senior executive would entail firefighting the various aspects of ensuring that the resource supply chain, the production value chain, the logistical processes, and the internal systems are all aligned to each other and any disturbance to one does not overly burden the entire business decision making capabilities. In other words, this business decision maker’s challenge is to ensure that each of these intricate parts of the business’s systems work like well lubricated parts in a machine and that the entire apparatus does not grind to a halt because of friction between them. This is especially important when the resources are being procured from different locations, manufactured in dispersed factories, shipped to all parts of the globe, and consumed wherever the value addition is the most and all supported by an IT backbone that maps each of these chains and provides the business decision maker with a bird’s eye view of the entire process.

Exploring these aspects in greater detail, we find that designing failsafe systems would entail drawing up business continuity plans, preparing the workforce to continue business as usual with minimal downtime, coordinating with and communicating to the stakeholders without leaving anyone, and then ensuring that the flow in the value chain is unimpeded. This means that the business decision maker has to decide on which components of the value chain are most critical so that there is zero downtime for them, prioritizing the activities so that the most crucial are identified leading to more resources being dedicated to them, designing the IT backbone in such a manner as to ensure that risk and especially high risk events are flagged immediately. Indeed, one of the most important aspects of tying in all these disparate and discrete processes into a coherent and comprehensive business system is the bottom line requirement of the process of designing a failsafe system.

Next, since we have discussed the aspects of designing failsafe systems, we can now turn to how resilient the system needs to be and how efficient it is to absorb shocks and recover from failures. For instance, the business decision maker we spoke to underscored how early warning systems are absolutely necessary for decision making since being alerted about potential downsides and risks as early as possible is in everyone's interest. This is the reason why many global corporations insist on their employees at all levels to escalate emergencies and even preempt major blowouts (literally as well as figuratively) to their higher-ups before they turn to full-fledged showstoppers.

While the reason for this is to avoid downtime as much as possible another reason for this is that in this 24/7 age of breaking news culture, it is better for the decision makers to know about potential disruptions from their own employees and managers instead of from the media. Indeed, this is the reason why many global corporations have established a clear chain of command which is activated in times of emergencies so that information flows from the bottom to the top, decisions from the top to the bottom, and feedback both ways is fed back into the loop. As mentioned earlier, one of the key requirements of failsafe business decision making is communication channels being kept open at all times so that there is no data black hole where decision and analysis paralysis sets in leading to more loss for the business.

3.2 The Need for Certainty and Control over the Future in Decision Making

Decision-making is a process that involves responding to short term and immediate term events and incidents as well as strategizing for the longer term with plans that are more sustainable and durable. This mix of reactive decision making in response to changing threats and proactive decision making that is geared towards the longer term is what makes the lives of business leaders that much more challenging.

Whether one is responding to the immediate events or one is strategizing for the future, the bottom line is that one is trying to get a grip on the external forces that impact the organization and hence, one is trying to find certainty in an increasingly uncertain world. The last phrase is important as unlike earlier eras, where decision makers could confidently predict and plan for the longer term, secure in the knowledge that the future is under control, decision makers in the 21st century have to live with extremely short duration plans, where the rapid pace of change and the sheer complexity of the business landscape means that they are subject to the pulls and pressures of the present which leaves them with no energy for the future. Even when they have a reasonable grip over the present, they are not sure what would happen when and where in the future which would leave them vulnerable to sudden shocks and Black Swan Events that are high impact, low probability occurrences.

The point that is being made here is that the need for certainty and control over the future determine the actions of the decision makers in the 21st century. This need for speed and the desire to stand triumphant over the longer term manifest themselves in the ways decision makers confront the business landscape. In order to actualize these objectives, decision makers turn to a variety of tools and techniques that help them plan for the future. This has led to an exponential increase in the demand for the services of futurists and market experts who publish dedicated newsletters and advisories to help the decision makers. In some cases, these experts consult exclusively and extensively with companies where the demand for their services arises from the fact that the business leaders want more control over their future. Indeed, the business of consulting has seen a dramatic surge as more and more companies try to understand the forces shaping the future and want the experts to guide them on strategies to harness them for their purposes.

3.3 Volatility, Uncertainty, Complexity and Ambiguity (VUCA) Paradigm for Leadership

3.3.1 The Volatility, Uncertainty, Complexity and Ambiguity (VUCA) Paradigm

Business leaders in the 21st century operate in a vastly different terrain than those who led their companies to success in the earlier decades. The landscape that confronts the business leaders of today is characterized by what is known as the VUCA principle or the Volatility, Uncertainty, Complexity, and Ambiguity characteristics.

This term has been coined by the noted futurist and member of the Institute for the Future, Robert Johansen, who points to the increasingly unstable and unpredictable world that the business leaders have to navigate. If we take volatility first, it is clear that consumer preferences and trends are ever changing and the rapid turnover in brands, products, and companies is proof that business leaders cannot take their leadership position for granted anymore. For example, the Finnish Mobile maker, Nokia that used to be the market leader a few years ago is now nowhere in the reckoning because astute and agile players like Samsung and Apple saw the emerging trend of Smartphones and quickly launched their products. As many people who watch cricket attest, one has to see the ball early and only then, one can hope to succeed. Similarly, the business landscape that is characterized by extreme volatility means that business leaders have to focus on getting there early and staying there for the future. In other words, business leaders have to channelize their energies so that they know the future to compete in the present.

3.3.2 Dealing with Complexity and Situations that Confuse and Muddle Decision Making

The next aspect of uncertainty is closely tied with the points made in the previous paragraph. Therefore, the next feature that is discussed here is complexity, which means that business leaders have to adopt a non-linear approach to solving problems and must think out of the box. Further, they would have to ensure that they not only solve the problems, but the business dilemmas brought on due to too much complexity which means that they would have to choose between several competing alternatives that are all attractive but cannot be actualized together.

The world has become so complex even for the layperson that the complexity in the business world is of much higher magnitude and is multilayered meaning that the landscape is now no longer a simple equation where profits mean success. In other words, the business leaders would have to ensure that they take into account the laws, regulations, and policies as well as social and environmental costs of doing business in an increasingly interconnected world where conditions in one region are markedly different from conditions in other regions.

3.3.3 Ambiguity and Out of Box Thinking

The fourth and the final aspect that business leaders must confront is ambiguity, which means that the business landscape presents problems and dilemmas that cannot be reduced to simple yes and no type of solutions and black and white approach to problem solving. Instead, most of the problems that business leaders face now are of the type where the complete information is lacking, where there are no clear solutions in sight, and where the reality of the marketplace is multilayered and multidimensional meaning that leaders would have to resort to unconventional ways of solving problems and confronting situations. Ambiguity also manifests in conjunction with the other features like uncertainty and complexity and as discussed next, each of these features feed into each other creating a mélange that is tough to handle for many firms.

3.3.4 Decision Making in a Confusing World

From the time we wake up to the time we finish for the day, we are bombarded with all kinds of facts, opinions, news, and views. In this context, the key imperative is to how to decide on anything to do with our daily lives without missteps and misjudgments. Decision making in a confusing world can be tough and this article discusses some strategies and tips on how to arrive at business or personal decision-making. The first and foremost aspect is that one must trust the source but must verify the facts. In other words, this means that one must not take everything that comes one’s way without ascertaining whether the information is true and relevant in addition to being pertinent and factual. This means that whenever we are presented with a particular piece of information, we need to double check and cross check it with other sources. A simple strategy here would be to cross check the information received from one source with other sources so that any possible misinformation can be vetted and verified. This works for most business leaders who often insist on multiple reports from different individuals so that they can make up their minds about the likely course of action. The point here is that we must not blindly trust all the information and use our sense of discretion and discernment when making up our minds.

The second aspect related to decision making in a confusing world refers to the ability to defer the decision without rushing into judgment and at the same time without delaying it too much. Research into behavioral decision-making indicates that it would be better to have a lag between the time the information is received and the time one makes the decision. In other words, look before you leap and take your time before arriving at a decision. The crucial window of time that is needed for successful decision making often makes the difference between success and failure.

Business leaders often take the time to listen to everyone’s point of view, and then ponder about the course of action to be decided, and then only arrive at a decision. In case on the spot decisions are required, and then rely on your experience and your judgmental abilities instead of relying on others. After all, if you are the decision maker, you would be held responsible for the consequences and not the others. Therefore, taking responsibility and having discernment are both admirable and advisable qualities in decision makers.

The third aspect is related to the need to keep one's eyes wide open meaning that one must actively seek information and knowledge from others. The best decision makers are those who equip themselves with the necessary knowledge and have the information about the macro issues at their fingertips. Most business leaders in the corporate world subscribe to think tanks and publications such as Harvard Business Review so that they are abreast of the latest happenings in the world of business. Apart from this, they actively seek feedback and listen to the other employees or the "boots on the ground" so that when they need to take a decision, the chances of them being misled by those with hidden agendas is minimal. One needs to remember that the corporate jungle or the euphemism for the corporate world resembles the metaphor and hence, success belongs to those who are astute, adroit, and agile. All these qualities need experience and an ability to synthesize information from different sources and to forge everything together into a cohesive and coherent set of data points that can be used as the basis of decision-making.

3.3 Decision Making Dilemma Managers Face: How to Grow Companies in a Time of Crisis ?

We discussed previously how decision making in these times is fraught with risk, uncertainty, and ambiguity. In this article, we examine a key dilemma facing managers in these times when economic conditions are gloomy. For starters, managers face the unenviable task of returning high profits in a time of inflationary pressures. This means that your company has to grow more than the prevailing rate of inflation if real returns have to be made. For instance, if the inflation rate is 10%, then the company's growth rate must be more than that and more importantly, the percentage increase in net profits must also be more than that if the real return on the capital has to be positive. This is the reason why some stocks perform well when compared to the others, as their real rates of return are more than the inflationary rate.

Next, managers also face the dilemma of rising costs of inputs, increased taxation, and competition from around the world. The point here is that since governments around the world are raising the taxes as a way to increase the revenues, which means that all the input costs go up leading to a cascading effect on the bottom lines of the companies. Further, with competition from lower wage and lower cost centres becoming more intense, managers in many multinationals and homegrown companies are faced with a situation where they have to not only grow more than the others, but also cut costs in the process. The point here is that companies can either increase bottom line numbers by increasing revenues and making more profits or cut costs to increase the profitability of their companies. The ideal scenario is where they can increase the profits and decrease costs at the same time, which would lead to Nirvana for the managers.

Finally, in recessionary times, companies have to do with consumers who spend less and demand more. This means that they have to contend with decreasing sales and increased discounts that have to be passed on to the consumers. Hence, the double whammy of decreased profits and decreased profitability means that managers have a tough task on their hands. Moreover, with less consumer purchases, deflation sets in where the prices are low but consumers do not have the money to spend. Hence, in any case, economic crises extract a heavy toll on companies and hence managers face a headache when confronted with decision-making choices.

Of course, the gloomy scenarios outlined here need not be the end of the world situations and there are ways and means to beat the gloom and ride the recession. Innovation is one aspect that companies can adopt to adapt to the tough market environment. Apart from that, companies can also optimize their current processes and reengineer their workflows so that efficiencies and synergies result which create new value for them. They can also rationalize their cost structures so that unnecessary and redundant expenses are eliminated. Finally, they can also focus on making their supply chains that much more effective and efficient.

3.4 Decision Making in Digital Age

We live in times when Information Overload is getting the better of cognitive abilities to absorb and process the needed data and information to make informed decisions.

In addition, the Digital Age has also engendered the Present Shock of Virality and Instant Gratification wherein decision makers do not have the luxury of taking decision after careful consideration and Due Diligence.

Indeed, when a Million Tweets and Facebook posts demand your urgent attention and require your instant responses, how can decision makers take the right, or for that matter, at least, notionally accurate decisions that address both the short term and the longer-term consequences of such decisions.

In short, being online all the time, and being subject to an endless barrage of digital knocks means that decision makers are often frazzled and left wanting.

This is the reason why many Political and Business Leaders often complain that the convergence of social media and Our 24/7 World is leading us to an abyss of Present Shock where everything happens at once and when decisions have to be taken in split seconds, which was earlier the domain of Combat Units.

Indeed, this is the reason why many leading American corporates are seeking the help of Navy SEALS and Defence Marines to help their Managers and Senior Executives navigate the tricky terrain that is modern decision making.

Apart from this, another Dilemma that decision makers have to confront is the consequences of their decisions in quick response times since the time lag between decisions and consequences is now measured in minutes and hours, rather than days and months.

This calls for a surprisingly high degree of Agility and Quick Thinking that soldiers are better at rather than staid Business Leaders in Pressed Suits.

Having said that, there are other aspects why decision making in the present times also needs a certain Zen kind of focus.

Indeed, this is the reason why many Spiritual Gurus are being asked to assist Business Leaders in developing the necessary Fortitude and Inner Strength to deal with the complexities of modern decision making.

For instance, quick decision making cannot be taken in a Troubled Frame of Mind. At the same time, decision makers have to avoid the Cognitive Dissonance Trap wherein there is a disconnect between their thoughts and actions.

Apart from this, Cognitive Biases and Emotional Triggers have to be set aside as well.

All this requires advanced levels of concentration and sagacity that only a Focused and Self Aware as well as a Calm and Composed person can.

Conclusion

When it comes to making decisions, one should always weigh the positive and negative business consequences and should favour the positive outcomes. This avoids the possible losses to the organization and keeps the company running with a sustained growth. Sometimes, avoiding decision making seems easier; especially, when you get into a lot of confrontation after making the tough decision. But, making the decisions and accepting its consequences is the only way to stay in control of your corporate life and time.

The vision and leadership qualities of the decision makers often play an important role in determining whether decisions result in zero sum situations or whether they result in everybody winning. The reason being it is the case that when decision makers take decisions that is based on their innate vision and leadership abilities, the result of such decisions often is that all the parties to the case are winners. This is the scenario where statesmen and leaders often take decisions by persuading the parties with their charisma and personality. Though this is the ideal situation that might or not might not manifest in reality, this is something that all of us can aspire to in our lives when we have to take decisions.

It is not always the case that decisions taken by the decision makers are perfect and free from errors. Hence, there has to be a mechanism where feedback loops have to be activated which ensures that decisions are vetted and evaluated for the impact that they have on the organization. So, to sum up the benefits of the OODA loop, it is indeed the case that this method developed by John Boyd is extremely useful for decision making in any setting where the reaction times are less and where the fitness and the agility of the decision maker plays a crucial part in making the decision. Taken together, the VUCA Paradigm is an apt metaphor for leaders who have to lead from the front and have to steer their companies through turbulent and choppy waters. As mentioned above, each of the features in the VUCA paradigm are interrelated and feed into each other with the result that the overall picture one gets is a business landscape that is chaotic, fluid, and ever changing. Indeed, this is where the true and great leaders can distinguish themselves from the rest of the pack through their vision and sense of mission.

Last, it is also the case that Business Schools incorporate these insights and theories from the West and the East in their curriculum so as to prepare the next generation of decision makers for the VUCA world or the world that is Volatile, Uncertain, Complex, and Ambiguous.

CHAPTER 4

THE IMPACT OF BUSINESS INTELLIGENCE THROUGH KNOWLEDGE MANAGEMENT

Introduction

Knowledge management (KM) is an important tool for the growth and competitiveness of any organization. Jelenic (2011) mentioned that KM is a vital resource for organizations of any size facing competition in any type of market. The amount of available data and the variety of their sources make it challenging to manage and use the resulting information for the benefit of the organization. Some companies utilize KM systems to manage complex knowledge. KM systems help organizations to identify patterns in data in order to create information and improve internal processes—such as the ones in financial, marketing, operations, and design managements—as well as those processes external to the organization. Nonaka (2007) presented in detail the significance of becoming a "knowledge-creating" company. Figure 2 illustrates the way in which knowledge transformations generate the foundation of *business intelligence* (BI). Nonaka (2007) strongly argued that knowledge creation is the key to continuous innovation and that knowledge can transform from tacit to tacit, explicit to explicit, tacit to explicit, and explicit to tacit

A *knowledge domain* encompasses knowledge from various elements of the internal and external environments. Shaikh, Bashar & Rafiq (2018) provide a list of elements within each category. They list competitors, information and communication technology (ICT), social networks, suppliers, distributors, government policies, and sustainability issues as the most prominent. The key elements of the internal environment are employees, resources, designers, planners, among others. Competitors are at the top of the list of external elements, indicating their significance. The knowledge surrounding this element is of paramount importance if the organization were to survive in the current business environment. The investment made in acquiring knowledge from competitors is part of an organization's BI. BI is therefore an inherent element of KM and experts utilize various tools to find valuable information to formulate internal and external business strategies.

Nielsen (2006) listed eight activities as parts of KM: knowledge creation, acquisition, capturing, assembling, sharing, integration, leveraging, and exploitation. He then categorized these activities into three dynamic capabilities such as knowledge development, knowledge (re)combination, and knowledge use. He argued that it is imperative to study BI in detail as well as the link between KM and BI. Figure 3 depicts the interactions between the two concepts.

Food processing is an emerging industry subjected to an important daily flow of information. Companies in this industry process agricultural products for public consumption or for ingredients in further processing. This industry includes the preservation of agricultural products as semi-dried products after initial or intermediate processing or as finished products (Pongpattanasili, 2004 p. 20). This study examined a food processing company in Algeria in order to understand the significance and usefulness of BI in this industry.

We structured the rest of the paper as follows. Section 2 presents an overview of BI followed by the link between KM and BI in Section 3. Section 4 presents the proposed hypotheses to be tested. Section 5 presents the conceptual model and methodological design followed by the data analysis in Section 6. Section 7 presents the discussion of results as a conclusion of the paper.

The global environment of a company is composed of several sectors such as the technological, institutional, political, economic, legal, sociological, and so on. It is evident that competition at the national and international levels is becoming increasingly more intense, and the competitive advantage that some organizations hold is comprised of only a few small differences. In simple words, *competitiveness* is the ability of an organization to face its competitors. It represents its long-term performance and growth based on three criteria: price, quality, and cost (Okamba et al., 2005 p. 18). It is well acknowledged that measuring and managing business performance is a challenging process. Rajnoha et al. (2016) presented BI as a key information and knowledge tool for strategic business performance management. They argued that due to fierce competition and the unpredictable environment, the organization needs to establish a surveillance and monitoring system for information collection to detect threats and seize opportunities. Information is therefore the pivotal element in the functioning of this system.

Section 1. The link between KM and BI

Several researchers (e.g., Cheng & Cheng, 2011; Weidong, Weihui, & Kunlong, 2010) provide comprehensive discussions on the similarities and differences between KM and BI. Cheng & Cheng (2011) concluded that KM and BI have a different system framework. They argued that organizations can benefit if the integration of KM and BI is based on their common characteristics. Walker & Millington (2003) provide a simple way to link KM and BI. One of the core elements of KM is capturing data, which can be accomplished using a variety of different tools. BI is one of the tools used in obtaining critical information that can immediately have an impact on an organization's strategies as well as its operational plans. Walker & Millington (2003) further confirm that inclusion of BI as part of KM practices has become a daily routine of KM personnel.

Cody et al. (2010) acknowledge that BI and KM are two technologies that have been vital in enhancing the quantitative and qualitative value of knowledge available for decision-makers. BI is about collecting relevant information from internal and external sources. The exponential growth in information and communication technologies has created opportunities to capture and disseminate information on a massive scale. At the same time, the abundance of data has created more challenges to finding the right information; therefore, KM has become crucial. It is important to screen the vital information and identify trends through different techniques such as data mining. Wang & Wang (2008) noted that data collected by a company are connected by unknown relationships and therefore the role of data mining is to find the interesting relationships among the data. Thus, improving knowledge means integrating data mining with knowledge management. Trninic et al. (2011) highlighted that contemporary business operations are based on BI in which data warehousing plays an integral part. They studied the significance and functional application of data warehouses in KM systems. They also argued that data warehousing can be an important basis for creating information, which can subsequently be used for knowledge acquisition.

The identified patterns and trends via data intelligence will be a source for counter-intelligence for organizations that can benefit from interventions. These interventions can be through design and development or even sales strategies. Researchers believe that the integration of BI and KM will be immensely helpful to organizations. The integration is done at three levels: presentation, data, and system (Weidong, Weihui and Kunlong, 2010). While the immaturity of text analysis was once a noticeable drawback for integration, that issue has been resolved with the development of new advanced technologies.

BI combines data gathering, data storage, and data management with analytical tools to present complex internal and external information to planners and decision-makers (Negash, 2004). Negash (2004) argued that BI is a set of coordinated actions of research, treatment, and distribution of information that can help economic factors but it is neither a product nor a system. It is an architecture and a collection of integrated operations—as well as decision-support applications and databases—that provide the organization easy access to business data. The roadmap of BI specifically addresses decision-support applications and databases (Moss & Atre, 2003 p. 4).

Shehzad & Khan (2013) identified a number of critical success factors related to both BI and KM technologies from the literature and assessed their effectiveness with similar research studies. They proposed a KM model that is comprised of the operational layer, the BI and KM layer, and the output layer. They demonstrated that the KM and BI components interact with each other to provide users with a comprehensive output. The concept of real-time BI is also studied in the literature and several models have been proposed. Alsuwaidan & Zemirli (2015) posited that KM is much needed in real-time BI applications in order to facilitate decisions during critical times. They proposed a model for integrating KM capabilities into a real-time BI process.

As noted by Herschel (2005), KM deals with both tacit and explicit knowledge while BI normally focuses on explicit knowledge. He studied the importance of integrating KM and BI, distinguished between these two elements, and provided the argument that BI improves knowledge. He also argued that KM and BI both contribute in building the intellectual capital of an organization. The obvious benefits of enhanced knowledge are enhanced decision-making and organizational performance (Herschel, 2005; Mchenry, 2005; Weidong, Weihui and Kunlong, 2010). Vinekar et al. (2009) also confirmed that the combination of BI and KM provides better support for decision-making. They elaborated that, while BI identifies the potential weaknesses and opportunities, KM supports the design, implementation, and process monitoring. Measuring and managing business performance is a challenging process. Based on the findings of this study, the key tool for increasing the overall economic performance of a company is to employ a strategic performance management tool supported by a knowledge-based BI.

Section 2. Application

2.1 Proposed Hypotheses

According to the literature, BI can defined in different ways. One simple way to define it is as a process that includes two primary activities: getting data in and getting data out (Watson and Wixom, 2007). The BI process includes several phases: identification of information needs, information acquisition, information analysis, storage, and information utilization (Lönnqvist and Pirttimäki, 2006). As such, BI receives untreated information that must be classified according to established criteria and processed through human analysis in order to provide useful information (Negash, 2004). BI can also be considered as a moving process that must be adapted to the expectations of an organization (Olszak, 2016). BI is rapidly gaining popularity as organizational leaders are recognizing the importance of its contribution to accomplish strategic advantage (Watson and Wixom, 2007). BI is not only an effective tool in decision making in firms, but it is considered more efficient than material factors (AL-Shubiri, 2012). Thus, this study formulates the following hypotheses:

H1. There is a positive relation between the search of information and business intelligence.

H2. There is a positive relation between the utility of information and business intelligence.

H3. There is a positive relation between the treatment of information and business intelligence.

H4. There is a positive relation between information security and business intelligence.

Business analytics is one of the four major technology trends since the 2010s. Leading organizations acknowledge the significance of BI in business analytics and report that BI has gained attention in both the professional and academic fields (Chen, Chiang and Storey, 2012). Technological assets are the foundational capabilities necessary for achieving success in BI (Işik, Jones and Sidorova, 2013). The two objectives in the implementation of BI are consistency and transformation. Organizations adopting BI for data consistency use a comprehensive data collection strategy, whereas organizations adopting BI for transformation use a problem driven data collection strategy (Ramakrishnan, Jones and Sidorova, 2012). Trieu (2017) presented a literature review on BI and concluded that researchers normally focused on the conditions necessary for the success of BI while they ignored the probabilistic process that links the conditions. The most effective way to prove the importance of BI is to quantify and to measure it (Lönnqvist and Pirttimäki, 2006). Thus, this study hypothesizes the following:

H5. Business intelligence has a positive impact on the competitiveness of a company.

2.2 Conceptual Model and Methodological Design

Very few articles can be found about BI and the food processing industry. One case study was conducted at the National Foods Industry in Pakistan, where BI was developed to process raw data to give an overall representation of performance (Asif, Hina and Mushtaq, 2017). The process significantly reduced the time spent in processing data usage. The BI process was composed of three main phases: extraction of the dataset, transformation to appropriate data structures, and loading the data warehouse and the workflows (Asif, Hina and Mushtaq, 2017). This study aims at filling the gap in the literature by measuring the impact of BI in the competitiveness (COM) of an organization in the food processing industry, and by demonstrating a positive relation between BI and its four elements: the search of information (SEA), the utility of information (UTI), the treatment of information (TRE), and information security (SEC). This study adopted the structural model shown in Figure 4 to analyze the impact of BI on the competitiveness of the organization. The second-order model in Figure 4 represents the assumption that the common underlying second-order formative construct BI can account for the seemingly distinct but related first-order constructs: SEA, UTI, TRE, and SEC. The latent variables: SEA, UTI, TRE, SEC, and COM constitute reflective measurement models (for simplicity not shown in Figure 23).

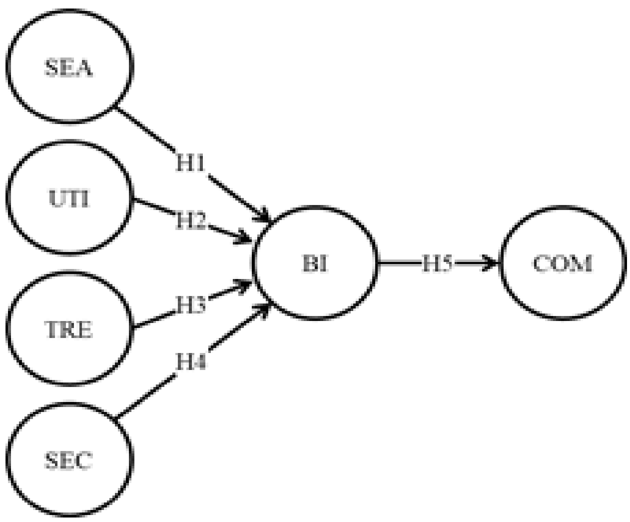


Figure 23.BI is a second-order construct while SEA, UTI, TRE, and SEC are first-order constructs.

The questionnaire given in Table 2 was adopted for this study and it consists of twenty items grouped under five variables. The first four constitute the BI elements while the fifth variable is the competitiveness. By filling the questionnaire, the respondents expressed their choice of disagreement or agreement according to a five-level Likert scale. The answer “strongly disagree” was coded as 1, the answer “rarely agree” coded as 2, the answer “neutral” coded as 3, the answer “somewhat agree” coded as 4, and the answer “strongly agree” coded as 5.

Table 2. Questionnaire composed of five variables: SEA, UTI, TRE, SEC, and COM.

Experience : □ 0-5 years □ 5-15 years □ 15- 25 years □ 25 years and over

Educational level: □ Basic □ Secondary □ University

Hierarchical level: □ Executive Officer □ Senior Executive □ Executive Agent

Variables	Items
Search for information (SEA)	SEA1. Collecting data in the business environment, such as customer suppliers and competitors, is essential
	SEA2. The layout of the tools (internet watch, subscription database, newsletter, etc.) facilitates the data collection
	SEA3. The organization of the collected information improves their use
	SEA4. Sharing of information between staff is important
Utility of information (UTI)	UTI1. The information collected is used to improve the positioning of the company
	UTI2. The information collected is used to improve customer expectations
	UTI3. Keeping watch over its environment serves to detect the threats and opportunities
Treatment of information (TRE)	TRE1. The Information and Communication Cell periodically analyzes the information collected
	TRE2. Internal databases, the intranet and the display, organize the dissemination of information within the company
	TRE3. The company can influence authorities and organizations to preserve these interests
	TRE4. The information collected allows innovation in the distribution, production, "servuction" and management of the company

Information security (SEC)	SEC1. Sensitive information is exposed to risks (theft, destruction, counterfeiting, etc.)—Reversed scale. SEC2. The company has an information protection policy SEC3. The financial and forecast data is safe SEC4. It is essential to control the sensitivity of the information before communicating it SEC5. Your servers and computer workstations are sufficiently protected by software and security materials
Competitiveness (COM)	COM1. The market share of your company is great COM2. You offer the best prices on the market COM3. You have a good corporate image COM4. Your business has the ability to face the competition

The subjects of the study were 30 upper level management personnel of the Western Regional Commercial Direction of Cevital Food Company (Cevital Group). Cevital Group is the first Algerian private company with 18,000 employees spread over four continents: Africa, Europe, Asia, and South America (Cevital, 2016). It represents the flagship of the Algerian economy. The company has crossed important historical stages to reach its current size and a favorable reputation in the food, electronics, steel, automotive, and other industries. The Group has world-class production units equipped with the most advanced technologies and its strategy is based on strong competitiveness regarding price, quality, volumes, logistics, robotization, and co-location. Research and development, innovation, and the talent of its contributors are always the company's top priorities. These competitive advantages form the basis of a dynamic and attractive industry that creates jobs for Algerian youth.

2.3 Data Analysis

This study used partial least square-structural equation modelling (PLS-SEM) to analyze the data. PLS-SEM is a second-generation statistical method suitable for situations in which the theory is not yet well developed and the primary objective for applying structural equation modelling is to predict and explain the target constructs (Rigdon, 2012; Hair *et al.*, 2017). PLS-SEM is a nonparametric method (no distribution assumptions) that generally achieves high statistical power even with small sample sizes. Given the characteristics of this study in terms of its theoretical background and data sample, PLS-SEM seems to be the appropriate choice. This study used the software package SmartPLS 3 to perform the data analysis using PLS-SEM. The model tested in this study has five latent variables with reflective measurement models, i.e., the exogenous variable SEA, UTI, TRE, and SEC and the endogenous variable COM. The model also has a second-order formative construct, BI, that is assumed to be "caused" by the four exogenous variables SEA, UTI, TRE, and SEC.

A preliminary examination of the outer loadings revealed that there were a few indicators whose outer loadings are somewhat below the threshold of 0.70. These indicators are: SEA3, TRE4, SEC1, SEC2, and COM4. Upon closer examination of these indicators, this study realized that there are legitimate reasons to delete these indicators. For example, indicator SEA3 "The organization of the collected information improves their use," was originally categorized as part of the search of information construct. In the minds of the readers, this indicator seems to reflect what is done with the information and not the actual search of the information. Likewise, in the indicator TRE4 "The information collected allows innovation in the distribution, production, 'servuction' and management of the company," the word "servuction" (the neologism constructed from the words "service" and "production"), might not have been fully understood by the readers. Similar rationale can be applied to justify the deletion of the other indicators. To assess the revised measurement models this study evaluated internal consistency, convergent validity, and discriminant validity. Table 3 shows the results summary after evaluating for internal consistency reliability, convergent validity, and discriminant validity of the reflective measurement models. We analyze each criterion below.

		Convergent Validity			Internal Consistency Reliability		Discriminant Validity	
Latent variable	Indicator	Loadings > 0.70	Indicator reliability > 0.50	AVE > 0.50	Composite reliability > 0.60	Cronbach's alpha > 0.70	Cross-loading (Max)	Fornell-Larcker criterion
SEA	SEA1	0.788	0.621	0.677	0.862	0.769	0.536	0.823
	SEA2	0.767	0.588				0.439	
	SEA4	0.907	0.823				0.786	
UTI	UTI1	0.955	0.912	0.846	0.943	0.908	0.655	0.920
	UTI2	0.935	0.874				0.618	
	UTI3	0.867	0.752				0.705	
TRE	TRE1	0.755	0.570	0.680	0.864	0.762	0.503	0.824
	TRE2	0.815	0.664				0.589	
	TRE3	0.898	0.806				0.718	
SEC	SEC3	0.952	0.906	0.768	0.908	0.872	0.562	0.876
	SEC4	0.898	0.806				0.266	
	SEC5	0.769	0.591				0.125	
COM	COM1	0.830	0.689	0.648	0.844	0.749	0.460	0.805
	COM2	0.926	0.857				0.650	
	COM3	0.629	0.396				0.601	

Table 3……………….

To evaluate internal consistency this study used the traditional two criteria of Cronbach's alpha and composite reliability. Cronbach's alpha provides an estimate for the reliability based on the intercorrelations of the observed indicators, while the composite reliability takes into account the different outer loadings on the indicators. Both measures are reported since Cronbach's alpha is a conservative measure of reliability while composite reliability tends to overestimate the internal consistency reliability. Table 3 shows that both the Cronbach's alpha and composite reliability measures exceed the typical thresholds. These values indicate that the reflective constructs have appropriate levels of internal consistency reliability.

To evaluate the convergent validity of the reflective constructs, this study considered the outer loadings of the indicators and the average variance extracted (AVE). High outer loadings on the constructs indicate that the associated indicators have much in common (captured by the respective constructs), and that they show sufficient levels of indicator reliability. AVE is the grand mean value of the squared loadings of the indicators (indicator reliabilities) associated with the constructs. Table 3 shows that the outer loadings of the reflective constructs are all above the threshold of 0.70 and that the AVE values for the reflective constructs exceed the minimum level of 0.50. Thus, the sets of indicators of the five reflective constructs have high levels of convergent validity, i.e., they are good measures of their respective concepts.

To evaluate discriminant validity of the indicators, this study examined the cross-loadings and the Fornell-Larcker criterion. Each indicator's outer loading on the associated construct should be greater than any of its cross-loadings on the other constructs. The Fornell-Larcker criterion compares the square roots of the AVE values with the latent variable correlations. Table 3 shows the maximum values of the cross-loadings on the other constructs of each indicator. Comparing each indicator's outer loading to the corresponding maximum cross-loading on the other constructs suggests that discriminant validity has been stablished based on this criterion. Table 3 also shows the square root of the AVE values for the constructs. By comparing the square root of the AVE values with the latent variable correlations (not shown in Table 3), it can be observed that the square root of the AVE value of each construct is greater than the construct's highest correlation with any other construct. Thus, the Fornell-Larcker criterion provides an additional indication of discriminant validity.

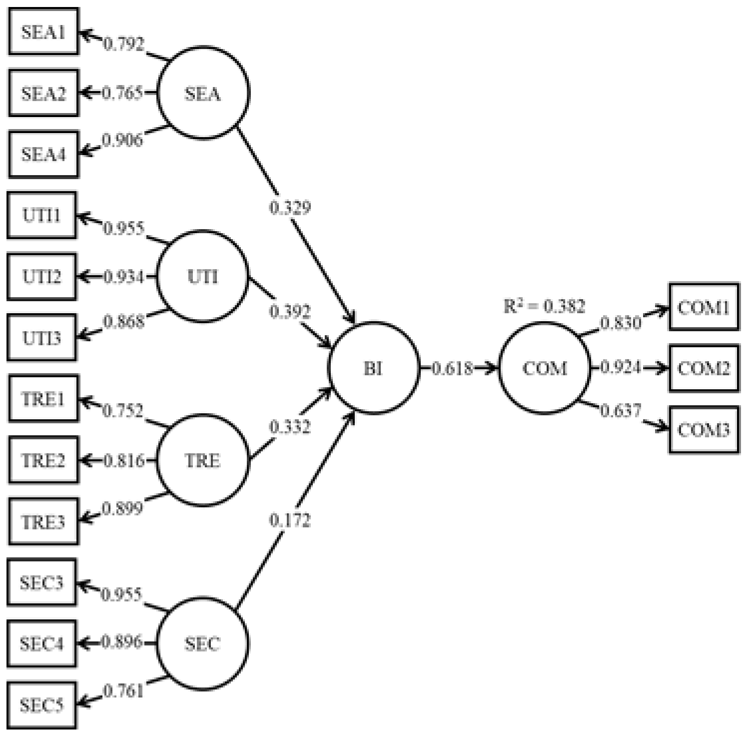


Figure 24.Structural model results.

Figure 24 shows the path coefficients and the R^2 value of the endogenous contract. Before analyzing these results, is it necessary to perform a more detailed assessment of the PLS-SEM results. This study first checked for collinearity by examining the variance inflation factor (VIF) values of all the sets of predictor constructs in the structural model. Table 4 shows that the VIF values of the combinations of endogenous constructs and corresponding exogenous constructs are all between the acceptable range of 0.2 < VIF < 5. Thus, collinearity among the predictor constructs is not a critical issue in the structural model. This study then examined the coefficients of determination (R^2 values) of the endogenous constructs. The R^2 value for the BI construct is 1.000 by definition while the R^2 value for the COM construct (0.382) is deemed moderate in this context. This study then considered the effect sizes f^2 for all structural model relationships. The f^2 value for all combinations of endogenous constructs and corresponding exogenous construct is 0.618 which is higher than the rule of thumb of high effect size ≥ 0.35.

Table 4.Miscellaneous results summary for the structural model.

Collinearity Statistics (VIF)

Construct	Inner VIF	
	BI	COM
		1.000
COM		
SEA	2.012	
SEC	1.260	
TRE	2.805	
UTI	2.294	

Summary of q^2 Effect Sizes

	BI	COM
SEA	–0.059	0.084
UTI	0.072	–0.057
TRE	0.007	0.006
SEC	–0.188	–0.012

To assess whether the path coefficients in Figure 5 and the total effects are significant, this study ran the bootstrapping procedure with 5,000 bootstrap samples, bias-corrected and accelerated bootstrap, two-tailed testing, and a significance level of 5%. Assuming a 5% significance level, this study fond that all relationships in the structural model are significant. Table 4 shows the bootstrapping report with the path coefficients and total effects including bootstrap mean values, standard deviation, *p* values, and 95% confidence interval bias-corrected.

Table 5.Significance testing results of the structural model path coefficients and total effect.

Path	Original Sample	Sample Mean	STD	*p* Values	95% Confidence Interval
BI à COM	0.618	0.644	0.088	0.000	[0.386, 0.754]
SEA à BI	0.329	0.318	0.066	0.000	[0.188, 0.446]
SEA à COM	0.203	0.207	0.056	0.000	[0.088, 0.305]
SEC à BI	0.172	0.168	0.072	0.017	[0.032, 0.300]
SEC à COM	0.106	0.108	0.047	0.024	[0.012, 0.188]
TRE à BI	0.332	0.324	0.037	0.000	[0.266, 0.409]
TRE à COM	0.205	0.208	0.034	0.000	[0.143, 0.274]
UTI à BI	0.392	0.386	0.054	0.000	[0.307, 0.533]
UTI à COM	0.242	0.247	0.044	0.000	[0.173, 0.346]

Finally, this study ran the blindfolding procedure to assess the predictive relevance of the path models with an omission distance $D = 7$. The final Q^2 values which judge the model's predictive relevance with regard to each endogenous construct are above zero, i.e., BI (0.389) and COM (0.187). These results provide clear support for the predictive relevance regarding the endogenous latent variables. Table 4 shows the results of the q^2 effect sizes with respect to all the relationships in the model. These q^2 effect sizes are considered small to medium.

Conclusion

Overall, the data analysis conducted above confirmed hypotheses H1 (0.329, p = 0.000), H2 (0.392, p = 0.000), H3 (0.332, p = 0.000), and H4 (0.172, p = 0.017). That is, the search of information, the utility of information, the treatment of information, and information security have a positive and significant relationship with business intelligence, i.e., these are four different elements "forming" BI. The data analysis also confirmed hypothesis H5 (0.618, p = 0.000), i.e., business intelligence—as a whole—has a positive, important, and significant influence on the competitiveness of the company. Furthermore, the second-order model was able to explain 38.2% of the variation of the competitiveness of the company. Thus, the model and the instrument seem to be appropriate for conducting this type of study.

In particular, by analyzing the path coefficients in Figure 4, this study fond that UTI is the most important element of BI followed very closely by TRE and SEA. This study also find that SEC has the least influence on business intelligence. These findings were somewhat expected since in the opinion of the company's personnel, the usefulness (utility) of the information is the BI element that can potentially create the most value for the company, i.e., increase its competitiveness. The company could also benefit from an increase in the perception of the security of information, perhaps by improving its practices in this area. More interesting, though, is the examination of the total effects on the competitiveness of the company. Table 4 shows the total effects of the four predecessor constructs, UTI (0.242, p = 0.000), TRE (0.205, p = 0.000), SEA (0.203, p = 0.000), and SEC (0.106, p = 0.024) on COM via the second-order construct, BI. The total effects of UTI, TRE, SEA, and SEC follow the same pattern of importance as their effects on BI discussed above. That is, UTI seems to be the BI element that influences COM the most while SEC influences it the least. By inspecting the outer weights (not shown) it can be identified that scale items SEC4 "It is essential to control the sensitivity of the information before communicating it" and SEC5 "Your servers and computer workstations are sufficiently protected by software and security materials" have the lowest outer weights. The company could benefit from addressing these two aspects of information security.

In summary, the competitive advantage of information cannot be derived from untreated raw information, and the fact of collecting and organizing information does not systematically generate competitive advantage. All data must pass through the process of BI within the KM framework and only then useful and exploitable information, considered as intelligent, offers this advantage to a company. It has to be noted that BI is an embedded element in the big picture of KM. The use of BI as a tool is fundamental in KM for the creation of new knowledge and combining it with the existing knowledge. The value provided by BI through KM is promising. Recall that KM is the process of managing knowledge while BI is the process that transforms raw information into intelligent and useful information for decision-making. This empirical study demonstrated a positive relationship between the elements: search of information, utility of information, treatment of information, information security, and business intelligence, as well as the impact of business intelligence on the competitiveness of a company.

CHAPTER 5

SIMPLIFIED ANALYTIC HIERARCHY PROCESS (SAHP) FOR BUSINESS DECISION MAKING

Introduction

Analytic Hierarchy Process (AHP) is a method for organizing and analyzing decisions, using mathematics and psychology. It was first introduced in 1977 By the work of Dr. Thomas L. Saaty in the Journal of Mathematical Psychology He first illustrated this theory on some examples for which the answers were known to allow for direct validation of the approach. The goal was to derive weights for a set of factors, also called activities, according to their importance. Where, the importance is numerically obtained according to several criteria

Since it's introduction, the AHP has evolved in different forms and shapes. The method consists of breaking a problem down and then aggregating the solutions of all the subp-roblems into a conclusion. It facilitates decision making by organizing perceptions, feelings, judgments, and memories into a framework that exhibits the forces that influence a decision. In the simple and most common case, the forces are arranged from the more general and less controllable to the more specific and controllable. The AHP is based on the innate human ability to make sound judgments about small problems.

According to Emrouznedjad &Marra, AHP is gaining extension in field applications. It was deployed in the higher education sector to improve the quality of education and universities' decision-making process. In the health sector, AHP appears to be an engaging tool to evaluate treatment strategies. In computer science applied to chemical engineering AHP is usefulness. In the energy sector, a multiplicative version was proposed to support group decisions in climate change negotiations. AHP combined with SWOT (strengths, weaknesses, opportunities and threats) analysis to support forest management planning and decision-making was applied in ecology.

In the late sixties and at the University of Pennsylvania, Dr. Thomas Saaty repeatedly observed difficulties in communication between researchers and lawyers and a significant lack of systematic approaches that can be used in practice to help prioritizing alternatives and criteria for decision making. Having seen the difficulty experienced by the top researchers and lawyers, Dr. Saaty was motivated to develop a simple yet effective way to help ordinary people make complex decisions based on solid mathematical basis.. The result was the Analytic Hierarchy Process, well known as the AHP method. Due to its capability to be applied for a wide range of fields, the AHP was largely accepted and adopted in the United States and later on, the rest of the world [4].

According to [5] Herbert Simon was early to note that the amount of information is growing rapidly, and that gaining access to information is not the biggest challenge organizations are facing. The biggest challenge in our estimation is the optimization of the outputs generated from the processed data. The tools dedicated to transfer the qualitative data into quantitative are rare. The Analytical Hierarchy Process (AHP) is a multi-criteria problem-solving method, It is widely used by decision makers for more than fifty years. It was first developed by Thomas Saaty, one of the pioneers of decision-making research in the world. The AHP is a meticulous method that allows the quantification of subjective criteria.

Section 1. Methodology

AHP uses pairwise comparisons to evaluate the weights. To perform a pairwise comparison, the decision-maker had to compare two items and determine their performance according to a scale. This comparison is repeated for every pair of items to generate a matrix. The matrix is used to generate relative weights. The repetition of comparing every pair of items reduces the risk of inaccurate results. (Forman and Gass, 2001). Basically, AHP is a method of breaking down a complex problem [6]. Another work, [7] used AHP method to conclude that transport is a significant criterion for optimal evacuation in crisis.
AHP addresses the problem of measuring intangible qualitative data. Understanding the AHP method on the first try is a bit challenging. The goal of developing this new tool-method in particular cases is to increase and facilitate the use of decision-making tools for the simple user.

The proposed method, SAHP, provides to the decision-maker a tool facilitating the process of transforming the qualitative data into quantitative and as a result the tool classify criterions compared to the first important criterion. The method deviates from the well-known Analytic Hierarchy Process AHP.

The SAHP is particular case of AHP method based on the following steps:

- The creation of (n) fictitious case equal to the number of criterions
- In each case, a single criterion dominates over the others (i.e., dominant factor).
- Adapting the same calculations as proposed by the AHP.
- Ranking the criterion according to their importance (see explanatory schema).

For example, an employer wants to recruit one candidate among two;

- The intangible qualitative data are:

The first candidate has a good sense of communication, but a bad sense of organization

The second candidate has a bad sense of communication and a good organizational skill.

- The quantitative data (see table 3)

Making a decision in a scientific method based on the intangible qualitative data which are the sense of organization and the sense of communication is a challenging task, this kind of challenge that our new SAHP method solves.

Table 6.Illustrative example of qualitative and quantitative criteria for the decision-making process.

	Qualitative		**Quantitative (years)**	
Criteria	Sense of communication	Sense of organization	Studies	Experience
Candidate 1	Good	Bad	5	0
Candidate 2	Bad	Good	3	10

The proposed method will reduce decision-making time, facilitate decision-making and classify qualitative factors according to their importance.

In order to determine a classification of factors according to their importance we provide a novel methodology that shares some similarities with the AHP method. Figure 25 presents a diagram to explain the methodology of the Simplified Analytic Hierarchy Process to classify the factors according to their importance.

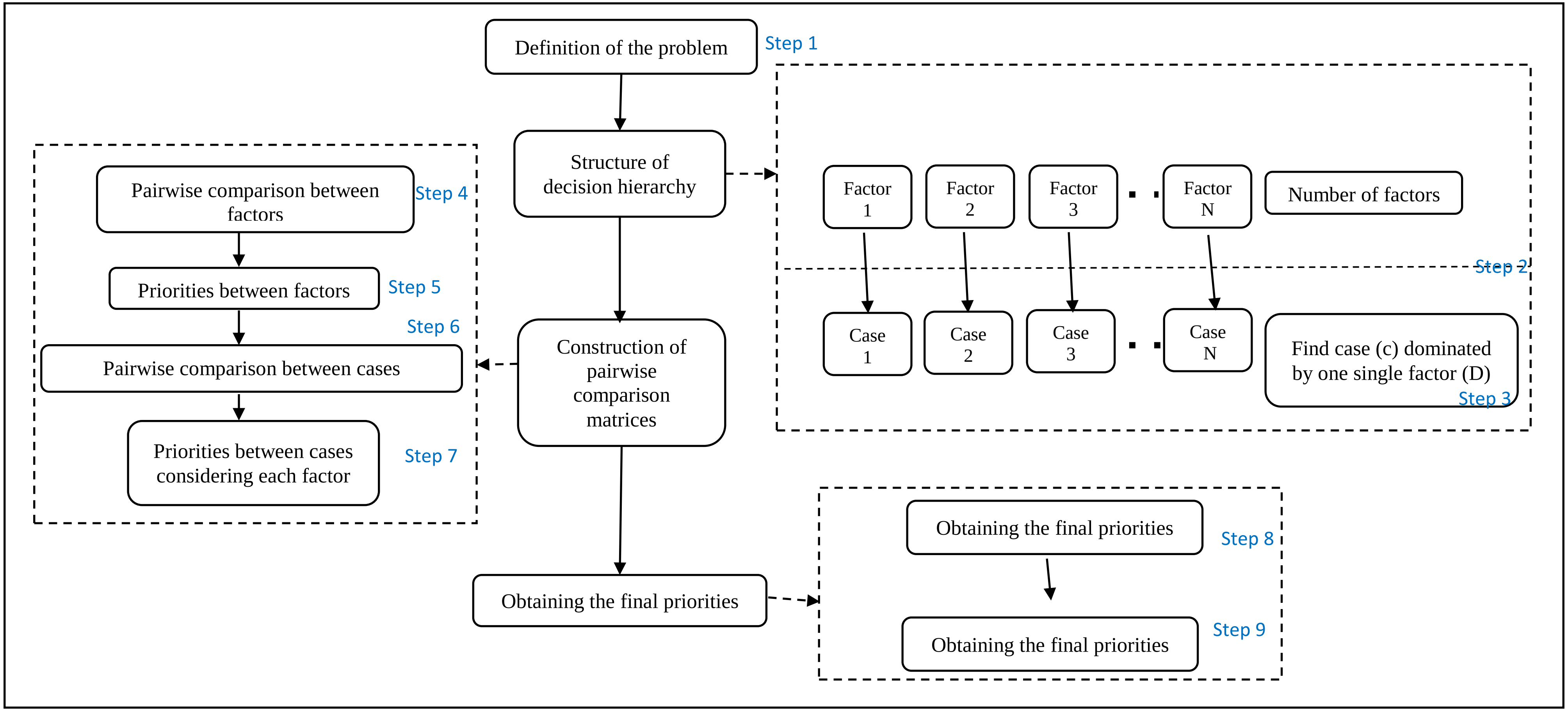


Figure 25.Diagram of the Simplified Analytic Hierarchy Process (SAHP).

Section 2: Modelling

1.1 Formulas of priorities between cases considering the dominant factor:

- **Formula of priority for the dominant factor:**

$$Pd = \frac{Id}{(N-1)+Id}$$

- **Formula of priority for the neutral factor:**

$$Pn = \frac{1}{(N-1)+Id}$$

P: $priority\ between\ cases\ considering\ the\ factor$

I: $intensity\ of\ importance\ of\ the\ factor$

d: $dominant\ factor$

n: $neutral\ factor$

N: $number\ of\ factors$

1.2 Formulas of final priority:

$$FPx = \frac{\sum_{x=1}^{N} \ Px + (N-1)Px}{(N-1) + Id}$$

FP: $Final\ Priority$

$x\ is\ the\ item\ number$ (i.e., 1, 2, 3, 4)

1.3 Proof of formulas

2.1. Formulas of priorities between cases considering the dominant factor:

- **Proof:**

Table 7: intensity of importance of each factor

intensity of importance of the factor	Extreme importance		Very strong importance		Strong importance		Moderate importance		Equal importance	
Factor	Pd	Pe	Pd	Pe	Pd	Pe	Pd	Pe	Pd	Pe
Priority	$\frac{9}{X+8}$	$\frac{1}{X+8}$	$\frac{7}{X+6}$	$\frac{1}{X+6}$	$\frac{5}{X+4}$	$\frac{1}{X+4}$	$\frac{3}{X+2}$	$\frac{1}{X+2}$	$\frac{1}{X}$	$\frac{1}{X}$

- **Formula of priority for the dominant factor:**

$$Pd = \frac{Id}{(X-1)+Id}$$

- **Formula of priority for the equal factor:**

$$Pe = \frac{1}{(X-1)+Id}$$

P: $priority\ between\ cases\ considering\ the\ factor$

I: $intensity\ of\ importance\ of\ the\ factor$

D: $dominant\ factor$

E: $equal\ factor$

X: $number\ of\ factors$

1.2 Formulas of normalised priorities:

- **Proof :**

Extreme importance

$$NP1 = \frac{9Pf1+Pf2+Pf3+Pf4+Pf5}{X+8}$$

$$NP2 = \frac{Pf1+9Pf2+Pf3+Pf4+Pf5}{X+8}$$

$$NP3 = \frac{Pf1+Pf2+9Pf3+Pf4+Pf5}{X+8}$$

$$NP4 = \frac{Pf1+Pf2+Pf3+9Pf4+Pf5}{X+8}$$

$$NP5 = \frac{Pf1+Pf2+Pf3+Pf4+9Pf5}{X+8}$$

- **Formula :**

$$NPx = \frac{\sum_{x=1}^{x} Px + (X-1)Px}{(X-1) + Id}$$

NP : $Normalised\ Priorities$

Both the similarities and the differences are summarized in Table 8.

Table 7.Similarities and differences between SAHP and the conventional AHP.

	Steps	Similarities	Differences
Definition of the problem	Step 1: Definition of the problem	Both methods require a clear and precise definition of the problem and its boundaries	/
Structure of decision hierarchy	Step 2 : Number of factors		1.In the AHP method, the decision maker has a number of alternatives to choose between them considering a number of criteria and subcriteria 2.In the SAHP method, the decision maker has one set of factors to be classified according to their importance.
	Step 3: Find case (c) dominated by one single factor (D)		In the SAHP, the decision maker doesn't have alternatives, he has a set of factors and the number of cases is equal to the number of factors that he needs to classify. Each case is mainly dominated by one dominant factor.
Construction of pairwise comparison matrices	Step 4: Pairwise comparison between factors	In both methods we proceed by constructing a pairwise comparisons based on personal judgment	1. The factors in the SAHP method are the equivalent of the criteria in the AHP method
	Step 5: Priorities between factors	The SAHP method uses the same form as the AHP method to calculate priorities in this step	
	Step 6: Pairwise comparison between cases	In both methods we proceed by constructing a pairwise comparisons based on personal judgment	1.The cases in the SAHP method are the equivalent of the alternatives in the AHP method 2.In the AHP method a personal judgement is needed to construct the pairwise comparisons 3.In the SAHP method a particular intensity of importance is given to the dominant factor in each case and an equal importance is given to the rest of factors called neutral factors

	Step 7: Priorities between cases considering each factor		1.The AHP method raises the matrix to large powers by summing each row and dividing each one by the total sum of all the rows. 2.The SAHP method uses priorities formulas : ● **Formula of priority for the dominant factor** $Pd = \frac{Id}{(N-1)+Id}$ ● **Formula of priority for the neutral factor** $Pn = \frac{1}{(N-1)+Id}$
Obtaining the final results	Step 8: Obtaining the final priorities		**Formulas of final priority:** $FPx = \frac{\sum_{x=1}^{N} \quad Px + (N-1)Px}{(N-1) + Id}$ The final priorities in the ICF-AHP is the equivalent of the normalised priorities
	Step 9: Obtaining idealised priorities	1. In both method we obtain the idealised priorities by dividing each final priority by the largest final priority	

Section 3: Application and results

According to a study published by The International Labour Office entitled "*Stimulating Youth Entrepreneurship: Barriers and incentives to enterprise start-ups by young people*".

There are five main factors for entrepreneurial engagement for youth:

1. Social and cultural attitude towards youth entrepreneurship;
2. Entrepreneurship education;
3. Access to finance/Start-up financing;
4. Administrative and regulatory framework;
5. Business assistance and support.

Table 8.Importance of factors in each case

Strength of Importance	Case 1	Case 2	Case 3	Case 4	Case 5
Social and cultural attitude towards entrepreneurship	Extreme importance	Equal Importance	Equal Importance	Equal Importance	Equal Importance
Entrepreneurship education	Equal Importance	Extreme importance	Equal Importance	Equal Importance	Equal Importance
Access to finance/Start-up financing	Equal Importance	Equal Importance	Extreme importance	Equal Importance	Equal Importance
Administrative and regulatory framework	Equal Importance	Equal Importance	Equal Importance	Extreme importance	Equal Importance
Business assistance and support	Equal Importance	Equal Importance	Equal Importance	Equal Importance	Extreme importance

Five cases were found, and each case is dominated by one single factor. The rest of the factors have an equal importance as can be seen on Table 5.

Table 9.Relative judgement between factors.

	Social and cultural attitude towards entrepreneurship	Entrepreneurship education	Access to finance/Start-up financing	Administrative and regulatory framework	Business assistance and support
Social and cultural attitude towards entrepreneurship	1	1/7	1/9	1/3	1/4
Entrepreneurship education	7	1	3	1/8	9
Access to finance/Start-up financing	9	1/3	1	1/7	9
Administrative and regulatory framework	3	8	7	1	9
Business assistance and support	4	1/9	1/9	1/9	1
Total	24	9.587	11.222	1.712	28.250

On Table 6, the factors on the left are compared with those on top using the fundamental scale of absolute numbers.

Table 10.Priorities between factors

	Social and cultural attitude towards youth entrepreneurship	Entrepreneurship education	Access to finance/Start-up financing	Administrative and regulatory framework	Business assistance and support	Priorities between factors
Social and cultural attitude towards youth entrepreneurship	0,042	0,015	0,010	0,195	0,009	0,054
Entrepreneurship education	0,292	0,104	0,267	0,073	0,319	0,211
Access to finance/Start-up financing	0,375	0,035	0,089	0,083	0,319	0,180
Administrative and regulatory framework	0,125	0,834	0,624	0,584	0,319	0,497
Business assistance and support	0,167	0,012	0,010	0,065	0,035	0,058

The priorities between factors are calculated using the AHP method (Table 6). The relative judgements between cases considering separately each factor from the following factors: social and cultural attitude towards youth entrepreneurship, entrepreneurship education, access to finance/start-up financing, administrative and regulatory framework and finally the business assistance and support (See the appendix section).

In each table, the factors on the left are compared with those on top using the fundamental scale of absolute numbers.

The Priorities between cases considering separately each factor from the following factors: social and cultural attitude towards youth entrepreneurship, entrepreneurship education, access to finance/start-up financing, administrative and regulatory framework and finally the business assistance and support.

The priorities between factors are calculated using formulas of priorities between cases considering the dominant factor

Table 11.The final priorities

	Social and cultural attitude towards youth entrepreneurship	Entrepreneurship education	Access to finance/Start-up financing	Administrative and regulatory framework	Business assistance and support	Priorities between factors	Final priorities	Idealised priorities
Case 1	0,692	0,077	0,077	0,077	0,077	0,054	0,110	0,288
Case 2	0,077	0,692	0,077	0,077	0,077	0,211	0,207	0,540
Case 3	0,077	0,077	0,692	0,077	0,077	0,180	0,188	0,491
Case 4	0,077	0,077	0,077	0,692	0,077	0,497	0,383	1,000
Case 5	0,077	0,077	0,077	0,077	0,692	0,058	0,112	0,294

The final priorities are calculated using formula of final priority (Table 11).

From the obtained results, it can be seen that administrative and regulatory framework is the main factor that impacts the entrepreneurial engagement for youth followed by the entrepreneurship education which represents 54 % from the importance of the first factor. Access to finance/Start-up financing represent 49.1 % from the importance of the first factor.

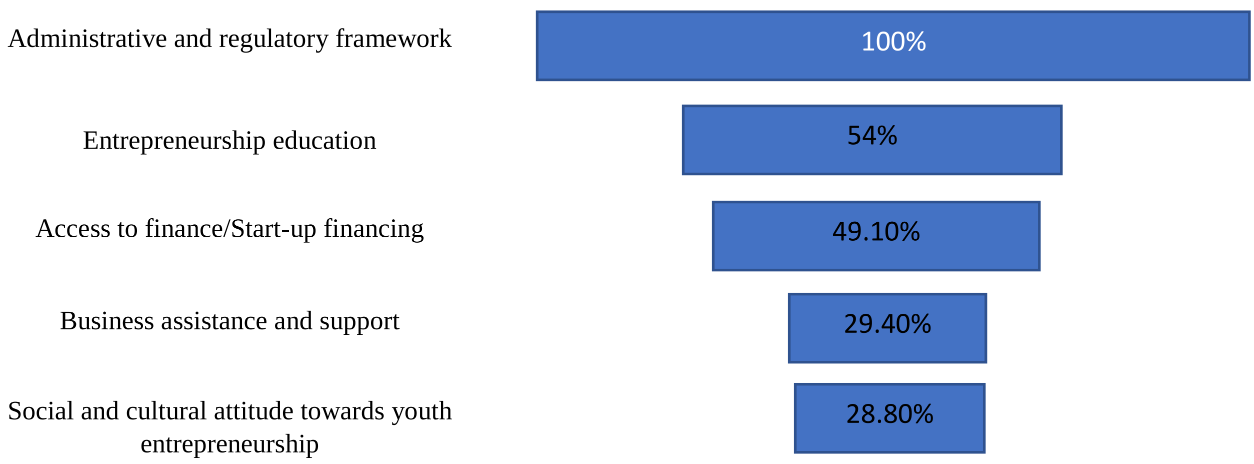


Figure 26.Tornado chart ranking the factors based on the SAHP method.

Business assistance and support represent 29.4 % from the importance of the first factor and Social and cultural attitude towards youth entrepreneurship is the last factor in our ranking and it represents 28.8 % from the importance of the first factor.

Conclusion

Progressing toward data-driven decisions in the business and entrepreneurial world requires simplifications of mathematical models to gain wide acceptance and applicability in the field. In this paper, the SAHP method is introduced. This method has the advantage of directly using available qualitative data, called factors, in a particular order. In this work, a numerical example is presented to show the applicability and performance of the method. The SAHP is proposed as an easy and quick method to prioritize factors based on simplistic assumptions. The upcoming work is an attempt to use fuzzy logic to capture data with a different nature while still focusing on the simplicity and a set of equations instead of the priority matrices.

General conclusion

Decision-making is important, not only in organizations, but in everyday life. Decisions are made on a daily basis, some which carry more weight than others, but it is imperative that leaders understand that the decisions made have an effect on individuals, and so there must be accountability for all those involved.

Decision-making is thinking through a process and coming to a consensus. Within organizations, decision-making affects stakeholders (i.e. vendors, customers, employees, shareholders etc.).

Leaders choose the best decision out of a set of good options or attempt to reduce harm from a set of bad options. This is ethical decision-making, so it is not enough to pick just one option, or two options.

The style is dependent on the problem (structured, unstructured, and crisis). Using the best style that fits the specific problem will render the best results. One tool that can be used within decision-making styles is the role of delegation.

Barriers of bounded rationality, escalation of commitment, time constraints, uncertainty, biases, and conflict can be detrimental to the decision-making process. Being knowledgeable about situations and using that knowledge can help remove barriers.

Teamwork, for the most part is beneficial, depending on the power dynamic. If too much power is presented, that needs to be evened out to ensure a full collaborative nature.

It forms the central part of the organization. Data-driven decision making is vital as it enables us to observe data from the actual time, the real time to come up with predictive insights. It provides the ability to research and know what is working well for the business and what is not.

Collecting and analyzing data, increase confidence in decision in any business challenge, whether it is about launching or discontinuing a product, adjusting marketing, branch into a new market, or something else entirely.

Data performs multiple roles. On the one hand, it serves to benchmark what currently exists, which allows to better understand the impact that any decision made will have on the business.

Beyond this, data is logical and concrete in a way that gut instinct and intuition simply aren't.

By removing the subjective elements from the business decisions the decision maker can instill confidence in his self and his company as a whole. This confidence allows the organization to commit fully to a particular vision or strategy without being overly concerned that the wrong decision has been made.

Just because a decision is based on data doesn't mean it will always be correct. While the data might show a particular pattern or suggest a certain outcome, if the data collection process or interpretation is flawed, then any decision based on the data would be inaccurate. This is why the impact of every business decision should be regularly measured and monitored.

When organization implement a data-driven decision-making process, it's likely to be reactionary in nature. The data tells a story, which the decision-makers and their organization must then react to. While this is valuable, it's not the only role that data and analysis can play within the business. Given enough practice and the right types and quantities of data, it's possible to leverage it in a more proactive way—for example, by identifying business opportunities before the competition does, or by detecting threats before they grow too serious.

There are many reasons a business might choose to invest in a big data initiative and aim to become more data-driven in its processes. Data analysis is, at its heart, an attempt to find a pattern within, or correlation between, different data points. It's from these patterns and correlations that insights and conclusions can be drawn.

The first step in becoming more data-driven is making a conscious decision to be more analytical. Both in business as well as in the personal life. While this might seem simple, it's something that takes practice. Whether in the office pouring over financial statements, standing in line at the grocery store, or commuting on the train, patterns are in the data around. Once noticed those patterns, practiced extrapolating insights and tried to draw conclusions as to why they exist. This simple exercise can help train our self to become more data-driven in other areas of our lifes.

Whenever a decision is about to be made, whether business-related or personal in nature, avoiding relying on gut instinct or past behavior when determining a course of action. Instead, making a conscious effort to apply an analytical mindset. Identifying what data is available that can be used to inform the decision. If no data exists, considering ways in which data can be collected. Once the data is there, analyzing it, and using any insights to help make the decision. As with the pattern-spotting exercise, the idea is to give enough practice that analysis becomes a natural part of decision-making process

Data visualization is a huge part of the data analysis process. It’s nearly impossible to derive meaning from a table of numbers. By creating engaging visuals in the form of charts and graphs, enable to quickly identify trends and make conclusions about the data.

Familiarizing with popular data visualization technique, and practicing creating visualizations with any form of data readily available. This can be as simple as creating a graph to visualize monthly spending habits and drawing conclusions from the visualization. Using these insights to make a personal budget for the next month. After completing that exercise, successful data-driven decision has been made.

While there are many benefits to data-driven decision-making, it’s important to note there is no need to take an all-or-nothing approach to get there. By starting small, benchmarking the performance, documenting everything, and adjusting on the go, the leader become more data-driven and thrive at the organization

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Appendices

Table A. 1: Priorities between factors

	Social and cultural attitude towards youth entrepreneurship	Entrepreneurship education	Access to finance/Start-up financing	Administrative and regulatory framework	Business assistance and support	Priorities between factors
Social and cultural attitude towards youth entrepreneurship	0.042	0.015	0.010	0.195	0.009	0.054
Entrepreneurship education	0.292	0.104	0.267	0.073	0.319	0.211
Access to finance/Start-up financing	0.375	0.035	0.089	0.083	0.319	0.180
Administrative and regulatory framework	0.125	0.834	0.624	0.584	0.319	0.497
Business assistance and support	0.167	0.012	0.010	0.065	0.035	0.058
	1.000	1.000	1.000	1.000	1.000	1.000

F1: Social and cultural attitude towards youth entrepreneurship

Table A2: Personal judgement between cases considering Social and cultural attitude towards youth entrepreneurship factor

	Case 1	Case 2	Case 3	Case 4	Case 5
Case 1	1.000	9.000	9.000	9.000	9.000
Case 2	0.111	1.000	1.000	1.000	1.000
Case 3	0.111	1.000	1.000	1.000	1.000
Case 4	0.111	1.000	1.000	1.000	1.000
Case 5	0.111	1.000	1.000	1.000	1.000
	1.444	13.000	13.000	13.000	13.000

Table A3: Priorities between cases considering Social and cultural attitude towards youth entrepreneurship factor

	Case 1	Case 2	Case 3	Case 4	Case 5	Priorities
Case 1	0.692	0.692	0.692	0.692	0.692	0.692
Case 2	0.077	0.077	0.077	0.077	0.077	0.077
Case 3	0.077	0.077	0.077	0.077	0.077	0.077
Case 4	0.077	0.077	0.077	0.077	0.077	0.077
Case 5	0.077	0.077	0.077	0.077	0.077	0.077
	1.000	1.000	1.000	1.000	1.000	1.000

Entrepreneurship education

Table A4: Personal judgement between cases considering Entrepreneurship education

	Case 1	Case 2	Case 3	Case 4	Case 5
Case 1	1.000	0.111	1.000	1.000	1.000
Case 2	9.000	1.000	9.000	9.000	9.000
Case 3	1.000	0.111	1.000	1.000	1.000
Case 4	1.000	0.111	1.000	1.000	1.000
Case 5	1.000	0.111	1.000	1.000	1.000
	13.000	1.444	13.000	13.000	13.000

Table A5: Priorities between cases considering Entrepreneurship education

	Case 1	Case 2	Case 3	Case 4	Case 5	Priorities
Case 1	0.077	0.077	0.077	0.077	0.077	0.077
Case 2	0.692	0.692	0.692	0.692	0.692	0.692
Case 3	0.077	0.077	0.077	0.077	0.077	0.077
Case 4	0.077	0.077	0.077	0.077	0.077	0.077
Case 5	0.077	0.077	0.077	0.077	0.077	0.077
	1.000	1.000	1.000	1.000	1.000	1.000

Access to finance/Start-up financing

Table A6: Personal judgement between cases considering Access to finance/Start-up financing

	Case 1	Case 2	Case 3	Case 4	Case 5
Case 1	1.000	1.000	0.111	1.000	1.000
Case 2	1.000	1.000	0.111	1.000	1.000
Case 3	9.000	9.000	1.000	9.000	9.000
Case 4	1.000	1.000	0.111	1.000	1.000
Case 5	1.000	1.000	0.111	1.000	1.000

Table A7: Priorities between cases considering Access to finance/Start-up financing

	Case 1	Case 2	Case 3	Case 4	Case 5	Priorities
Case 1	0.077	0.077	0.077	0.077	0.077	0.077
Case 2	0.077	0.077	0.077	0.077	0.077	0.077
Case 3	0.692	0.692	0.692	0.692	0.692	0.692
Case 4	0.077	0.077	0.077	0.077	0.077	0.077
Case 5	0.077	0.077	0.077	0.077	0.077	0.077
	1.000	1.000	1.000	1.000	1.000	1.000

Administrative and regulatory framework

Table A8: Personal judgement between cases considering Administrative and regulatory framework

	Case 1	Case 2	Case 3	Case 4	Case 5
Case 1	1.000	1.000	1.000	0.111	1.000
Case 2	1.000	1.000	1.000	0.111	1.000
Case 3	1.000	1.000	1.000	0.111	1.000
Case 4	9.000	9.000	9.000	1.000	9.000
Case 5	1.000	1.000	1.000	0.111	1.000
	13.000	13.000	13.000	1.444	13.000

Table A9: Priorities between cases considering Administrative and regulatory framework

	Case 1	Case 2	Case 3	Case 4	Case 5	Priorities
Case 1	0.077	0.077	0.077	0.077	0.077	0.077
Case 2	0.077	0.077	0.077	0.077	0.077	0.077
Case 3	0.077	0.077	0.077	0.077	0.077	0.077
Case 4	0.692	0.692	0.692	0.692	0.692	0.692
Case 5	0.077	0.077	0.077	0.077	0.077	0.077
	1.000	1.000	1.000	1.000	1.000	1.000

Business assistance and support

Table A10 : Personal judgement between cases considering Administrative and regulatory framework

	Case 1	Case 2	Case 3	Case 4	Case 5
Case 1	1.000	1.000	1.000	1.000	0.111
Case 2	1.000	1.000	1.000	1.000	0.111
Case 3	1.000	1.000	1.000	1.000	0.111
Case 4	1.000	1.000	1.000	1.000	0.111
Case 5	9.000	9.000	9.000	9.000	1.000
	13.000	13.000	13.000	13.000	1.444

Table A11: Priorities between cases considering Business assistance and support

	Case 1	Case 2	Case 3	Case 4	Case 5	Priorities
Case 1	0.077	0.077	0.077	0.077	0.077	0.077
Case 2	0.077	0.077	0.077	0.077	0.077	0.077
Case 3	0.077	0.077	0.077	0.077	0.077	0.077
Case 4	0.077	0.077	0.077	0.077	0.077	0.077
Case 5	0.692	0.692	0.692	0.692	0.692	0.692
	1.000	1.000	1.000	1.000	1.000	1.000

Table 12: The overall priorities

	Social and cultural attitude towards entrepreneurship	Entrepreneurship education	Access to finance/Start-up financing	Administrative and regulatory framework	Business assistance and support	Table 3: Priorities between factors	Normalised priorities	Idealised priorities	The rating
Case 1	0.692	0.077	0.077	0.077	0.077	0.054	0.110	0.288	5
Case 2	0.077	0.692	0.077	0.077	0.077	0.211	0.207	0.540	2
Case 3	0.077	0.077	0.692	0.077	0.077	0.180	0.188	0.491	3
Case 4	0.077	0.077	0.077	0.692	0.077	0.497	0.383	1.000	1
Case 5	0.077	0.077	0.077	0.077	0.692	0.058	0.112	0.294	4

Abstract

In the world of business, corporations of all sizes have been collecting data for decades, with or without having an idea on how and where to use it. Making use of these collected data, in its different forms, have the potential to boost fact-based innovation in corporations. The latter will help uncover new ideas and support business decisions with solid evidence. One of the biggest reasons why corporations need to use analytics to make better decisions is due to the risk being posed by the sheer amount of data being gathered.

In this thesis, we develop new models to work with data that are not necessarily quantitative in nature. Within these models, we investigate necessary and sufficient conditions on the practicality of data analytics. The results of our studies reveal that qualitative data can be transformed into quantitative data to feed analytical models for data-driven decision-making. Another concern raised by business analysts we interviewed was the complexity of these analytical models. To address this concern, one of our models aims to simplify the analytical hierarchy process. The proposed model is named SAHP, for simplified analytical hierarchy process. All the models presented in this thesis were tested on business cases and proven to be effective in incorporating business data into a business decision-making model based on evidence.

Keywords: Decision-making, Big Data, Risk, Business Intelligence, Competitiveness, Knowledge Management, Data tools, Data Analysis, AHP, SAHP

Résumé

Dans le monde des affaires, des entreprises de toutes tailles collectent des données depuis des décennies, avec ou sans idée de comment et où les utiliser. L’utilisation de ces données collectées, sous ses différentes formes, a le potentiel de stimuler l’innovation basée sur des évidences. Ce dernier aidera à découvrir de nouvelles idées et à soutenir les décisions commerciales avec des preuves solides. L’une des principales raisons pour lesquelles les entreprises ont besoin d’utiliser l’analyse des données pour prendre de meilleures décisions est le risque posé par la grande quantité de données collectées. Dans cette thèse, nous développons de nouveaux modèles pour travailler avec des données qui ne sont pas nécessairement de nature quantitative. Au sein de ces modèles, nous étudions les conditions nécessaires et suffisantes sur la praticité de l’analyse des données. Les résultats de nos études révèlent que les données qualitatives peuvent être transformées en données quantitatives pour alimenter des modèles analytiques pour la prise de décision qui est basée sur les données. Une autre préoccupation soulevée par les analystes commerciaux que nous avons interrogés était la complexité de ces modèles analytiques. Pour répondre à cette préoccupation, l’un de nos modèles vise à simplifier le processus de hiérarchie analytique. Le modèle proposé est nommé SAHP, pour un processus hiérarchique analytique simplifié. Tous les modèles présentés dans cette thèse ont été testés sur des analyses de cas commerciaux et se sont avérés efficaces pour incorporer des données commerciales dans un modèle de prise de décision commerciale basé sur des preuves.

Mots clés : Prise de décision, Big Data, Risque, Business Intelligence, Compétitivité, Gestion des connaissances, Outils de données, Analyse de données, AHP, SAHP

الملخص

تقوم المؤسسات بجميع أشكالها في عالم الأعمال بجمع البيانات لعقود من الزمن، سواء بغرض أو بدونه حول كيفية استخدامها ومكان استخدامها، إن استخدام هذه البيانات التي تم جمعها بأنواعها المختلفة، تساهم في تحفيز الابتكار القائم على الأدلة، مما سيساعد هذا الأخير في الكشف عن أفكار جديدة ودعم قرارات العمل مبنية على أسس متين، حيث أن أحد الأسباب الرئيسية التي تجعل المؤسسات تتجه إلى استخدام تحليلات البيانات لاتخاذ قرارات أفضل هو المخاطر التي يشكلها التدفق الكبير لهذه البيانات.

تهدف هذه الدراسة إلى تطوير نماذج جديدة للعمل مع البيانات بغض النظر عن طبيعتها، ومن خلالها ندرس الشروط الضرورية والكافية حول التطبيق العملي لتحليل البيانات، حيث توصلنا إلى أنه يمكن تحويل البيانات النوعية إلى بيانات كمية لتثمين النماذج التحليلية لصنع القرار المعتمدة على البيانات، كما أنه يوجد انشغال أخر أثاره محللو الأعمال الذين قابلناهم وهو مدى تعقيد هذه النماذج التحليلية، لذلك يهدف أحد نماذجنا إلى تبسيط عملية التسلسل الهرمي التحليلي في إطار ما يسمى بـ SAHP وتم اختبار جميع النماذج المقدمة في هذه الأطروحة على تحليلات دراسة الجدوى وأثبتت فعاليتها في دمج بيانات الأعمال في نموذج صنع القرار التجاري القائم على أسس وأدلة.

الكلمات المفتاحية: اتخاذ القرار، البيانات الضخمة، الخطر، ذكاء الأعمال التنافسية ، إدارة المعرفة ، أدوات البيانات ، تحليل البيانات ، عملية التحليل الهرمي، التسلسل الهرمي التحليلي المبسط.