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Improving decision making in the digital era: Human and Machine

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In an increasingly digital world, companies are subject to constant and fast changes that require prompt responses and strategic decisions. The technological advances that contribute to business pressures can also be a source of competitive advantage. For this, organisations need to improve the way they make decisions, supported by evidence and making good use of both human expertise and data. How can we optimise decisions in such an environment?

This thesis brings to the business world academic research results that often take a long time to be incorporated in work practices. Furthermore, it bridges the gap between the human study and technology, two integral components of decision making generally discussed in isolation. It addresses the question of how to improve decision making, taking into consideration flaws and potential of both humans and machines.

We take a look at human cognition, analysing how humans make decisions. Some limitations are derived from our senses or memories, others come from our cognitive processes and we act as if we had two brains, an impulsive one, affected by heuristics and biases, and a rational one. Combined with the powerful effect of emotions, we constantly deviate from rational models of decision makers. But we also excel at some intuitive decisions. Some of our shortcomings can be overcome by training and evidence-based decisions, nowadays, possibly driven by data. We describe artificial intelligence from the business perspective, how it can help make better decisions, but also has its faults. Both humans and machines will have to work together, augmenting each other's capabilities.

Keywords	decision making, digitalisation, human cognition, biases, heuristics, business intelligence, artificial intelligence

Contents

1 Decision making

The business environment is in constant change. While there are abundant examples of companies working at very fast pace, such as Apple or Zara, the jury is still out as to the pace of change really being increasing or not (The Economist, 2015). Nevertheless, changes in consumer power, awareness or brand loyalty (Searcey, 2014) are forcing businesses to shift from a production-oriented to a more consumer-oriented mind set, thinking first of what benefits the customers (King, 2002, p. 27; Perreault and McCarthy, 2013, Ch. 22). Technological advancements are allowing a more global communication and information exchange, increasing the pressure on organisations to respond quickly to environmental changes and consumer interactions, in particular in the instant gratification culture in which we see ourselves (Anderson and Raine, 2012). Therefore, companies that can better understand their customers, quickly react to their requirements, and keep a constant and personalised interaction with them can take the lead. This forces organisations to be agile and make constant strategic decisions. The same digital advances that contribute to the pressures placed on industries, are however also a source of competitive advantage, when used properly. With this intent, businesses may need to improve the way they make decisions, supported by better information and knowledge, often requiring large amounts of data processed even in real time and requiring computerised support (Sharda and Turban, 2014).

Decision making is the process of identifying problems and opportunities and selecting the course of action to deal with them, chosen from a number of possible alternatives. Some decisions are inherently difficult to make and often it is hard to know if we did the correct choice. It may be impossible to compare different ‘what ifs’ or to understand the causal connections in a complex world. Still, we attempt to make informed decisions that will come to positive results.

1.1 The digital transformation

The move towards evidence-based decisions is not new. The medical field has long been the stage for many of the developments that companies have more recently started to implement. Already in 1835, a critique on the use of statistical evidence was published, as recounted by Poisson and Larrey (2001), but decisions remained highly subjective for a long time. Hence, in 1979, the Canadian Task Force on the Periodic Health Examination published a list of levels of evidence, from opinions of authorities and descriptive studies (level III) to randomised controlled trials (level I).

Schools of strategic thought identify different possibilities for organisations, including strategies that can be planned and implemented following an individual's vision (*e.g.*, Mintzberg and Ahlstrand, 2005) and, although most managers use evidence in their decisions, often the quality of the evidence is not clearly assessed (Barends and Briner, 2014). This leads to bad decisions based on unsupported beliefs or fashions. When considering the available evidence, one should take into account *scientific* evidence from published and peer-reviewed scientific research; *organisational* evidence collected from the organisation; *experiential* evidence derived from own experience and judgment; and *stakeholder* evidence that includes the goals and concerns of all those affected by the decisions. But this evidence cannot be taken at face value without a critical assessment. The ability to gather information, understand its relationships and use the insight to guide decisions was described as Business Intelligence (BI). Perhaps the earliest use of this term was by Devens (1865, p. 210), with later references already being connected to the information technology world, by Luhn, an IBM researcher, in 1958 and, in 1989, a comeback of the term by Dresner, from Gartner (Power, 2007). Nowadays, according to Quaddus and Woodside (2015), companies either deploy BI systems or risk a position of disadvantage in relation to their competitors. Figure 1 depicts the business Pressures-Responses-Support model (Sharda and Turban, 2014), starting with the pressures businesses are facing through to the decision, supported by business intelligence.

In the middle of such a complex scenario, how can businesses incorporate the knowledge about human behaviour and performance, while, at the same time, keeping up to date with the technological advances? Additionally, this topic also becomes increasingly pertinent in face of recent political events that undermine the efforts for improving decision making,

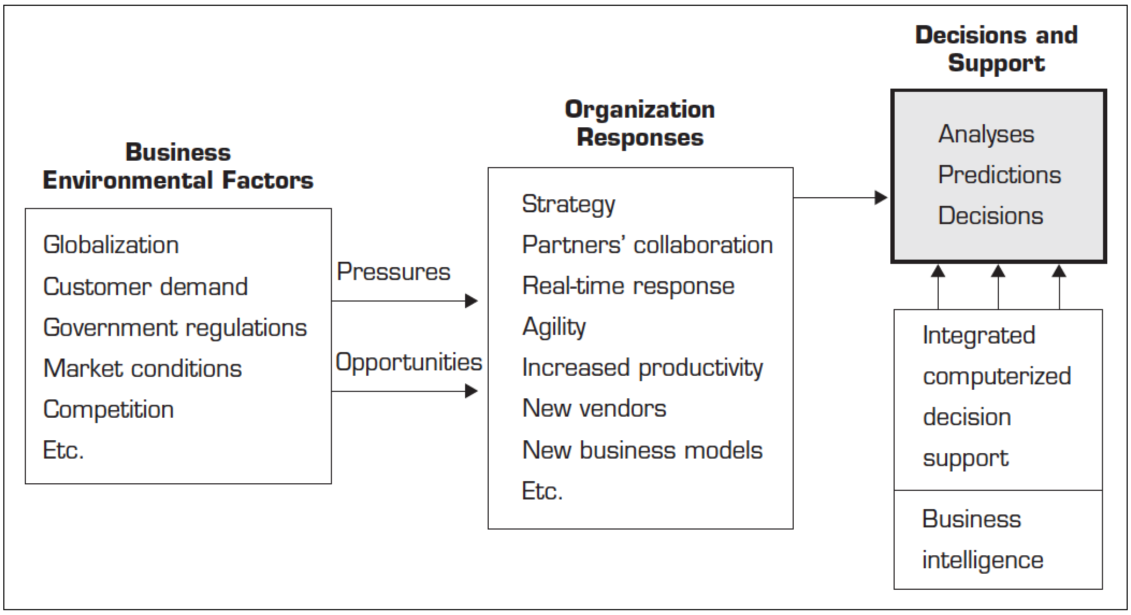

Figure 1: Pressures-Responses-Support model (Sharda and Turban, 2014) showing the context of decision making in organisations.

with, for example U.S. administration having told the Centre for Disease Control not to use expressions such as "evidence-based" or "fact-based" (Sun and Eilperin, 2017). Society is also facing changes and the technological transformation that allows people to connect and knowledge to be shared has also helped the "death of expertise" (Nichols, 2017). The right of opinion is being mistaken for the right to have an opinion as valid as anyone else's, journalism is forced to compete with entertainment and drawn to similar tactics (attempting to create viral stories, clickbait, *etc.*), and universities are looking at students as customers, forgetting their role in society[1]. All this is enhanced by the shift towards digital information and communication and permeates into the business world, affecting decision makers and companies.

1.2 Thesis motivation and scope

In light of the importance of decision making and the current changes, not only in the work place, but also in society, there were two main motivations for this work. The realisation that results from research usually take a long time to reach the general public and noticing

[1]Universities attempt to appease students who want to be shielded from debate and ideas that are challenging, controversial or cause discomfort (*e.g.*, Lukianoff and Haidt, 2015; Anthony, 2016) and, as fees rise, students see their education as being of "poor value" (Neves and Hillman, 2017).

that two integral components of decision making, the human and the technological, were often looked at in isolation. This thesis attempts to bring knowledge developments from the academic to the business setting and to bridge the gap between the human and the technology, under one reference document for decision makers.

The question being addressed is, **How can decision making be improved, taking into consideration strengths and failures of both humans and machines, in an increasingly digitalised world?**.

In order to explore this topic, we first start by looking at the different contexts in which decisions are made (Chapter 2). In Chapter 3, we explore the Human decider, the flaws and strengths of human cognition, and what influences decisions. In Chapter 4, we turn to the Machine as decision maker, not meaning by this only an entirely autonomous machine, but everything that has been used to support evidence-based decision making. The interaction between the two is discussed in Chapter 5 and possible improvements are presented in Chapter 6. Finally, Chapter 7 dares to peek into the future and Chapter 8 offers a brief conclusion of this still open topic.

2 Decision making context

We often face decision making scenarios in difficult conditions. The U. S. Army War College calls it VUCA, meaning *volatile*, *uncertain*, *complex* and *ambiguous* (Stiehm, 2010) and it can be applied to individuals, groups or organisations. This requires constant adaptation and a high degree of situational awareness, which is not a static picture of the environment, but also incorporates prediction and monitoring of its evolution.

In Figure 2 we can see that situational awareness is not the only factor acting on decisions. Individuals' performance is affected by their past experiences, own abilities or how well they can store and retrieve information. But other pressures, often unnoticed, can influence decisions, such as the person's goals (of which a business needs to have an understanding due to the principal-agent problem[2]), preconceptions or biases. In addition, also our interaction with machines can influence what we perceive and how we make

[2] This is a conflict of interests where one party, the agent, is supposed to act on behalf of the principal, but whose interests may not be aligned. (Eisenhardt, 1989)

decisions. Think, for instance, of how data are displayed, user experience with a certain software, interfaces, *etc*.

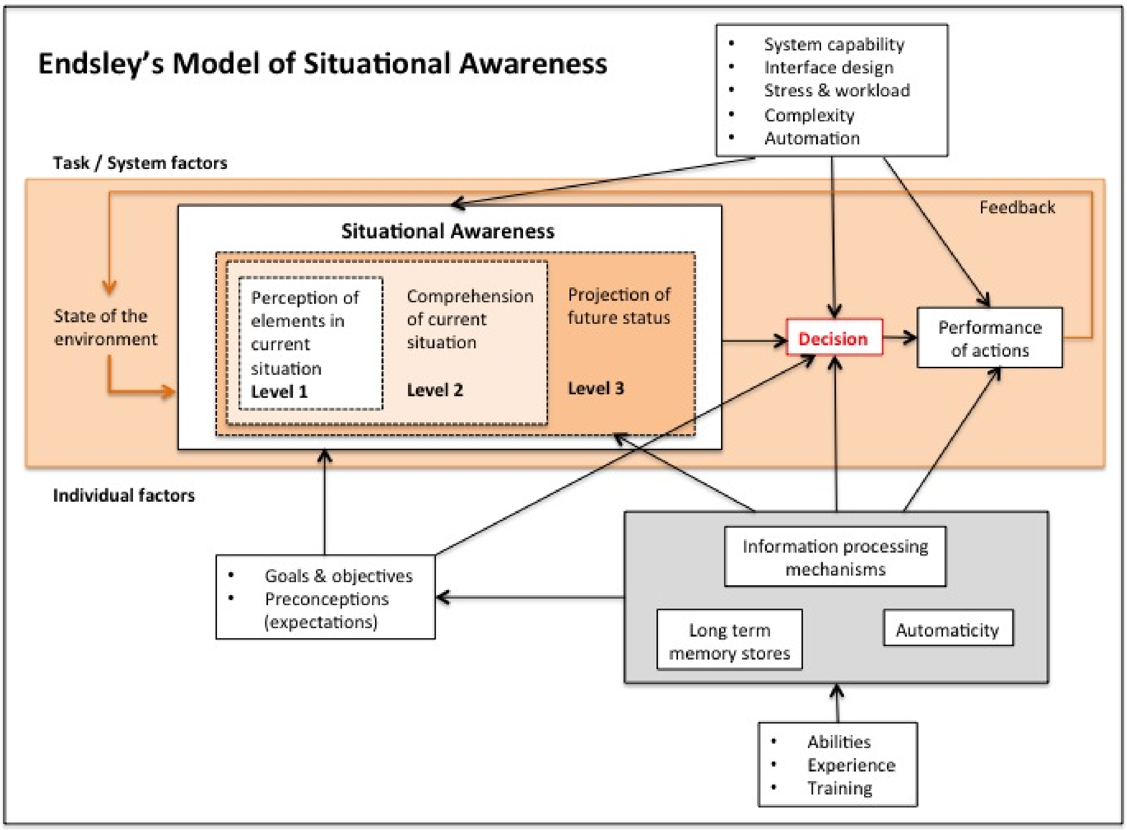

Figure 2: Situational awareness in dynamic decision making (Endsley, 1995).

Because of the complexity of the world around us, we tend to make simplifications that can lead us astray, such as using the model of the *economic man*, that can be applied both to us and to competitors, customers or any other entity. This means that when something happens, it must have been with intent and for a reason. But we know this is not always the case. Chance, coincidence, accidents happen. We also often assume there is a certain order in the world, that we can derive cause-effect relationships and that by knowing them we can (a) explain what has happened and (b) predict or lead something to happen. It is easy though to get lost among the myriad of signals that can be picked up nowadays, in particular with the advent of Big Data[3], or to confuse correlation with causation.

There are frameworks that attempt at identifying different scenarios and adjust the decision-making process. For example, in the Cynefin framework (Kurt and Snowden, 2003), represented in Figure 3, there are five domains:

[3]Big Data can be defined by the "Four Vs", volume, variety, velocity and veracity.

- a central one of disorder - should be minimised
- chaos (unordered) - no cause and effect relationships
- complex (unordered) - cause and effect are only discernible in retrospect
- knowable (ordered) - cause and effect relationships exist, but are separated over time / space
- known (ordered) - cause and effect relationships exist and are evident

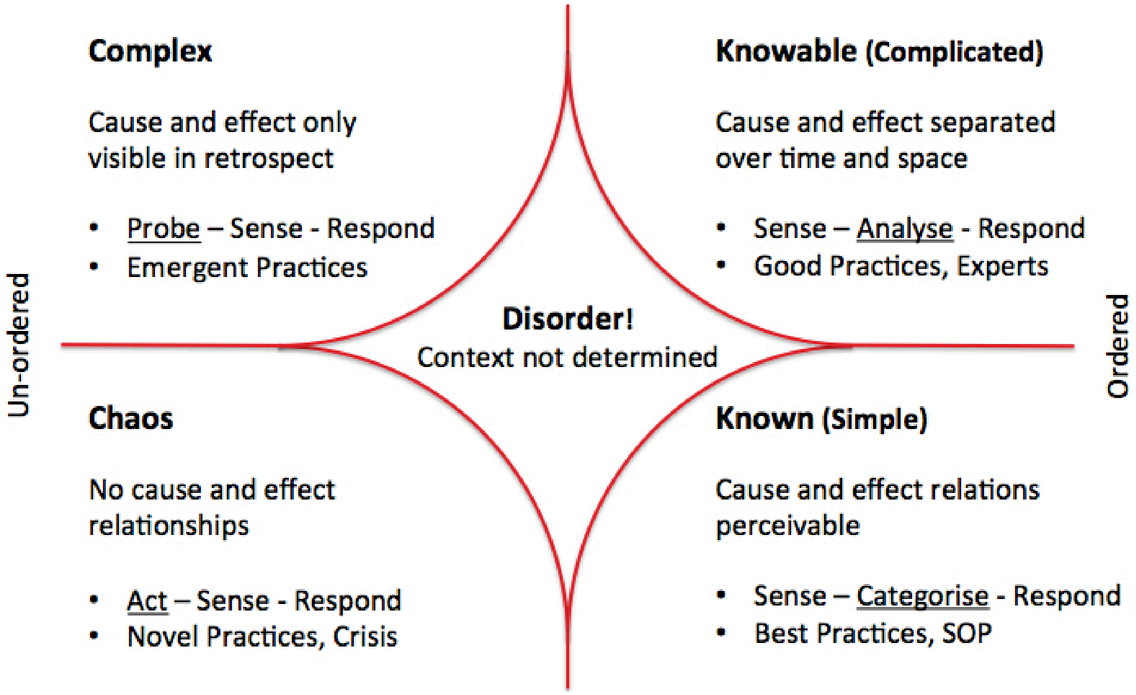

Figure 3: The sense-making Cynefin framework with the defining cause-effect relationship in each quadrant. The first point explains the advised course of action, highlighting the most important action. The second point gives examples of applicable practices.

Since the situations are different in nature, they also require a different decision-making process and actions. The **known** scenario is perhaps the simplest. One should sense the data, categorise it appropriately and respond according to best practices and standard procedures that can even be automated. In the **knowable** situation, there is a cause-effect relationship, but it must first be analysed and discovered. When facing **complex** scenarios, one cannot see the existing cause-effect relationships until after the fact. And when it happens, we must be careful with hindsight bias, which is discussed in § 3.3.2. What can be done is to probe the system, sense emerging patterns and respond accordingly. Finally, there is **chaos**, where no cause and effect relationships exist and where often one is in crisis management mode that requires an immediate action. This will produce a feedback that needs to be sensed and followed by an appropriate response. Seen that there are different possible scenarios that require different strategies, how aware are companies? Figure 4 identifies realistic statuses of how companies implement decision making.

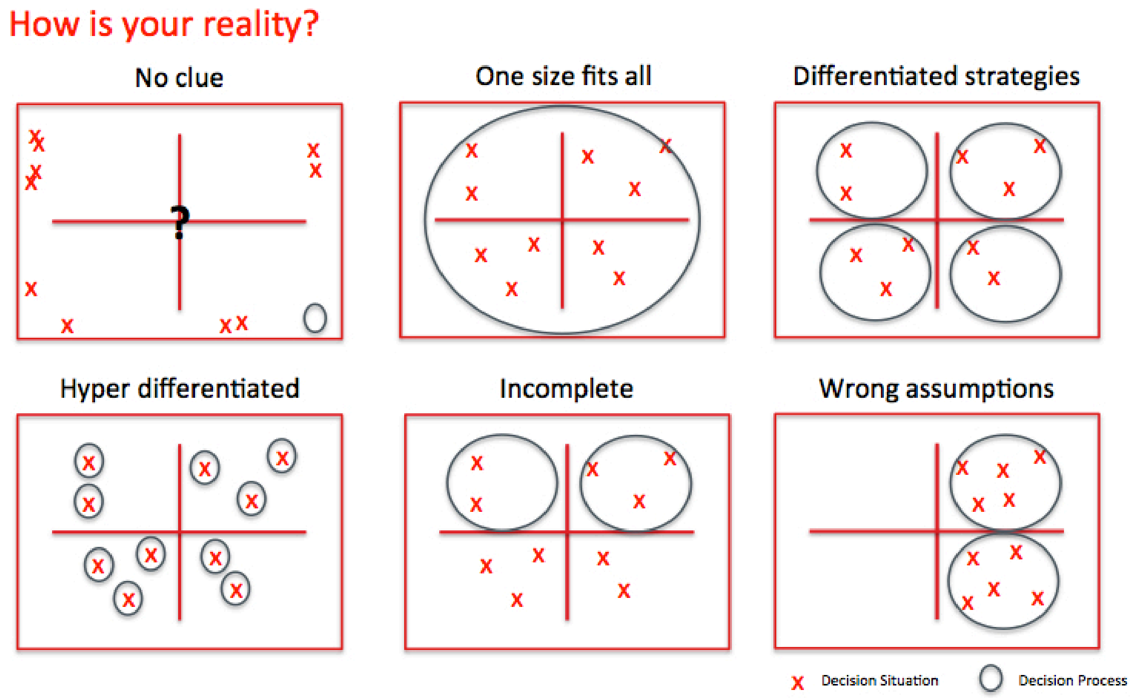

Figure 4: Different decision-making scenarios and strategies companies may have in place to face them, based on the Cynefin framework. The crosses denote decision situations recognised by the company and the ellipses denote existing decision processes to face those situations.

No clue - In this case there is a complete lack of awareness and strategy to face decision-making scenarios the company can face, which will lead to chaotic processes.

One size fits all - Or does it? There might be a process on how to approach decision needs, but a *one size fits all* strategy will not be optimal or not even fit many of the company's needs.

Differentiated strategies - In this situation, there is a recognition that different contexts require different approaches, guided by common features that increase the likelihood of making good decisions.

Hyper differentiated- There is the danger, though, of seeing each situation as unique and spending too much time and resources tailoring the process individually to them.

Incomplete - An incomplete vision is suitable for some circumstances, but unprepared to face others. It may be that the business mainly faces situations of a particular type, but even if less developed, strategies should exist to face all scenarios.

Wrong assumptions - In a more extreme way, a company may think not only that most their decision scenarios are of certain types, but that all their scenarios are of certain types. It is worth questioning the validity of such assumptions. In particular in a global world, where threats and opportunities can rise from far away and technological advances are changing many of the traditional ways of working.

2.1 Strategy validation

What happens when time goes by? In the Cynefin framework it is also possible to cross boundaries, either as situations evolve or purposely. In business life, though, often strategies are defined at specific times (quarterly, yearly) and followed without being revisited for some time.

Discussion often revolves around strategy planning and execution, sometimes even touching upon acceptance, which is of particular importance when change is involved. However, it is less often acknowledged that we live in a complex world, every day more interconnected, with social and economic changes, global competition and a myriad of risks distracting us. As much as we try to validate a strategy *a priori* through in-depth market research, data analysis and forecasts, we are still a part of an ever-changing ecosystem. There are also resource limitations influencing how much we can explore and sets of simplifying assumptions where these strategies are anchored.

While internal monitoring and management is a relatively established practice, companies do not always stay on top of what lies outside their control. They may be focused on following a set direction and meeting planned goals, but what if the correct decision is to change the plan? Do the initial assumptions still hold true? Is the environment still the same?

Aileron (2017) lists in Forbes 10 reasons for strategic planning failure. Among them are:

- not understanding the environment
- unwillingness or inability to change
- ignoring marketplace reality, facts, and assumptions

This means one should not blindly follow a plan that is already failing because, as Helmuth von Moltke the Elder puts it, “No battle plan survives contact with the enemy”. This is particularly important when the changes in the environment have been hidden by simplifying assumptions at the time decisions were made. Furthermore, following a planned vision leads to less success than keeping an open mindset for discovering new things along the way (Pontikes and Barnett, 2017). In practice, a long-term strategy should be complemented by an agile and constantly informed (what Kachaner and Kunnas (2017) from the Boston Consulting Group call “Always-on”) strategy and leadership. Treat your strategy less like a plan to follow and more like a hypothesis that needs to be kept in check.

Even when recognising different situations, having processes to deal with them and revisiting strategies to re-evaluate and validate them, there will always be a decision action that can be misguided, being it made by a person or aided by technology. Let us first look at how people perform.

3 Human

Common sense is very rare. - Voltaire

Common sense is often used as a justification for a course of action or decision. Not only it is not common, but also having a shared view does not make it real, it can still be nonsense. Following such convictions would fall more into the field of beliefs. What we often see is that those who challenge common sense are able to more accurately understand the world. This does no mean, of course, that any idea should be taken as valid and, unfortunately, we also see common sense as an argument defended by those who lack expertise and even as political ideology. There is a certain disregard for expert knowledge, as when the conclusions are easy to understand they are common sense, when they are counter-intuitive, they are deemed to be wrong Furnham (1983). In reality, we can rarely make use of our limited experience to draw reliable conclusions about the varied situations we encounter in life.

Are we rational beings? In Descartes' Error, Damásio (1994) showed that states of the body influence the mind. The *economic man*, a rational person who always acts to maximise personal utility and still used in economics has long been criticised for its lack of approximation to reality. Real people are more complex and simplifying them too much can lead to wrong predictions of behaviour. Surprisingly, the field of economics, despite dealing with people, for a long time did not attempt to understand how they really functioned. That was until psychology was brought in and behavioural economics started to be developed. It is, thus, necessary to understand the real decision-making human, not just a model of what it should be. It is also necessary to know if, recognising our shortcomings, can we be rational when needed?

Even if one tries to minimise the risks of subjectivity by removing the human from the process, this is seldom possible and can also be argued not to be wise. It is, therefore, necessary to better understand how humans process information and make decisions.

3.1 Fooled by our senses, tricked by memories

Before looking at how people think and analyse information in order to make choices, we have to look at the initial stages when information is being acquired and how we perceive the world around us. If seeing is believing, what are the consequences of seeing incorrectly? It is not new that we can be deceived by our senses. Figure 5 shows a well known illusion by Müller-Lyer (1889). Even after knowing the lines have the same length, we still cannot force our brains to acknowledge that fact.

Surprisingly, simple illusions like that are still being discovered (*e.g.,* Fig. 6)! And similar flaws can also happen with moving objects, where, for instance, motion-induced blindness can make us not see certain things (Grindley and Townsend, 1965).

Nowadays this problem is compounded by technological advances. Not only are people bad at recognising digitally altered images (Nightingale et al., 2017), but also artificial

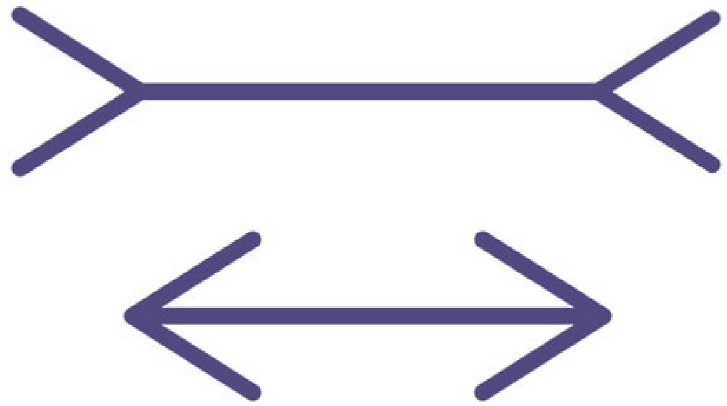

Figure 5: Representation of one of several optical illusions present in Müller-Lyer (1889). The length of the horizontal line on the top, with arrows pointing inward appears to be longer than the bottom line with arrows pointing outward despite being the same length.

intelligence is capable of “imagining” a scenario and generating images indistinguishable from reality (Fig. 7). This means extra effort will be needed to validate information.

Vision is so important to us that it can influence other senses. Deception can affect taste (*e.g.*, Acree, 2013), hearing (*e.g.*, the McGurk Effect, McGurk and MacDonald, 1976), or tactile sensations Botvinick and Cohen (*e.g.*, the rubber hand experiment 1998).

In addition, our perception is influenced by different factors (Fig. 8). Perception is information that a person is able to discern from the surrounding world. It is, therefore, a process by which one not only gathers, but also interprets it and to which one attaches a meaning. This plays an important part both immediately when assessing a situation and later when recalling stored memories.

Not only can we perceive things wrongly, but our ability to later recall events or information suffers from what Schacter et al. (2003) call the seven sins of memory (Table 1). Therefore, we must be careful in trusting our memories and should understand its limitations.

3.2 Rational choice theory

Individual decision making lies at the foundation of microeconomics. It looks at the behaviour of individuals and firms in a variety of areas, from consumption or savings to even

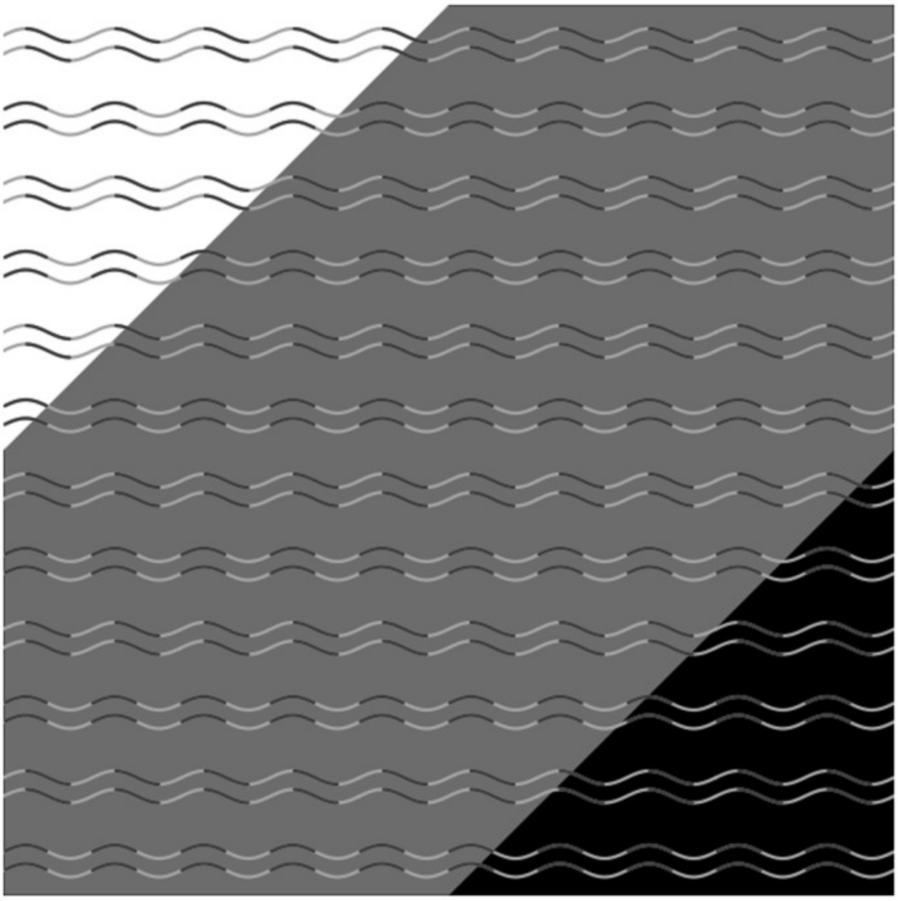

Figure 6: A wavy line is perceived as a zigzag line when the change between dark and bright sections of the line happens at the crest and trough (Takahashi, 2017).

Table 1: Seven sins of memory. The three first ones can be seen as being of a *forgetting* type, whereas 4-7 can be classified as *distortion*, and *persistence* as an *intrusion*.

	Sin	Description
1	Transience	Decreasing accessibility of memory over time
2	Absent-mindedness	Lapses of attention that result in forgetting
3	Blocking	Information is present, but temporarily inaccessible
4	Misattribution	Memories are attributed to an incorrect source
5	Suggestibility	Implanted memories about things that never happened
6	Bias	Current knowledge and beliefs distort memories of the past
7	Persistence	Unwanted recollections that we can never forget

decisions concerning marriage or having children (at the individual level) or investments, hiring practices or market entry / exit (at the firm level) and is usually supported by the Rational Choice Theory. In this approach, which has been a dominant paradigm in economics, individuals act with the intent to maximise the utility function. This function simply assigns a value to each of the possible choices available to the individual / firm, based on preference. With it come as well a set of constraints (for example, a budget).

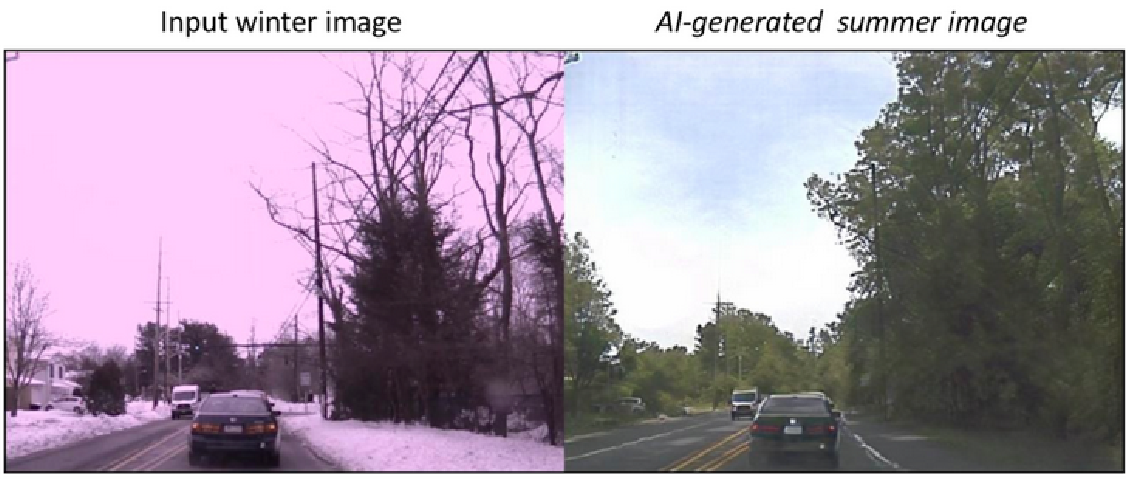

Figure 7: Same scene, original on the left and as “imagined” by artificial intelligence on the right (NVIDIA example based on Liu et al. (2017)).

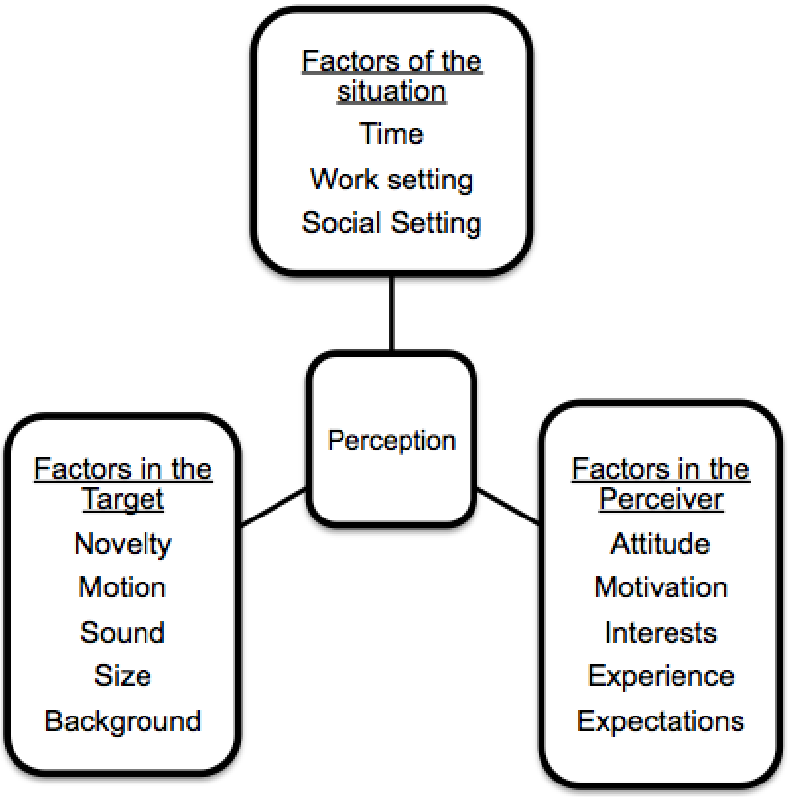

Figure 8: Factors influencing perception (Robbins et al., 2010).

Despite its widespread use, already in 1955, Herbert A. Simon argued that people act to “satisfice”, not optimise a certain decision scenario. This means a solution is good enough when it is satisfactory and sufficient. Furthermore, it may not always be possible to obtain all the information necessary to make the best decision. We have a limited knowledge of the world and of the nature of the problems, limited ability to process information, forecast and anticipate consequences of our actions, not be influenced by emotions, *etc.* (Simon, 2000). Simon called this scenario *bounded rationality*. We will see that, not only there can be opportunities for improvement, but that an apparently satisfying solution can be fundamentally wrong. Later, when developing their Prospect Theory, Kahneman and Tversky (1979) have also identified situations where behaviour did not match the principles of rational choice theory. Prospect theory shows, for example, that we weigh losses more than equivalent gains and this can be costly in the long run. We also feel regret and even the thought of this possibility influences decisions. Decision weights depart from outcome probabilities in ways that can turn people risk averse or risk seeking (Figure 9) depending on the gain / loss and the probability of the event happening. And choice can even change depending on how the scenario is presented. This should not happen to rational individuals.

		GAINS	LOSSES
HIGH PROBABILITY **Certainty Effect**	e.g.: Creates:	95% chance to win €10 000 Fear of disappointment RISK AVERSE	95% chance to lose €10 000 Hope of avoiding loss RISK SEEKING
LOW PROBABILITY **Possibility Effect**	e.g.: Creates:	5% chance to win €10 000 Hope of large gain RISK SEEKING	5% chance to lose €10 000 Fear of large loss RISK AVERSE

Figure 9: This figure, adapted from Kahneman (2011), shows how people display different risk profiles at odds with the probabilities of the events and possible outcomes.

3.2.1 Conscious choice

Not paying attention? Your brain is.

Rationality should require a conscious process of evaluation and critical choice. Even when we just follow a preference, a gut feeling or wishful thinking, we still like to believe that the choice is grounded on reason or try to rationalise it afterwards. But an experiment by Tusche et al. (2010) indicates that neutral evaluation of products and associated choice processing does not necessarily depend on attentional processing of the available items. The study involved measuring brain responses to exposure to different cars. While one group was specifically asked to evaluate and rate the different cars in order to make a choice, the second group was not only not told they would have to make a choice, but was also distracted from paying attention to the cars by being forced to perform other tasks. Nevertheless, the second group was subconsciously making choices that could be detected with functional magnetic resonance imaging (fMRI) and the choices could be equally well predicted in both groups (Fig. 10). These results put in evidence the existence of automatic and subconscious choices, ahead of deliberation and without paying much attention. Their findings highlight the potential of implicit, automatic processes in guiding even important and complex decisions.

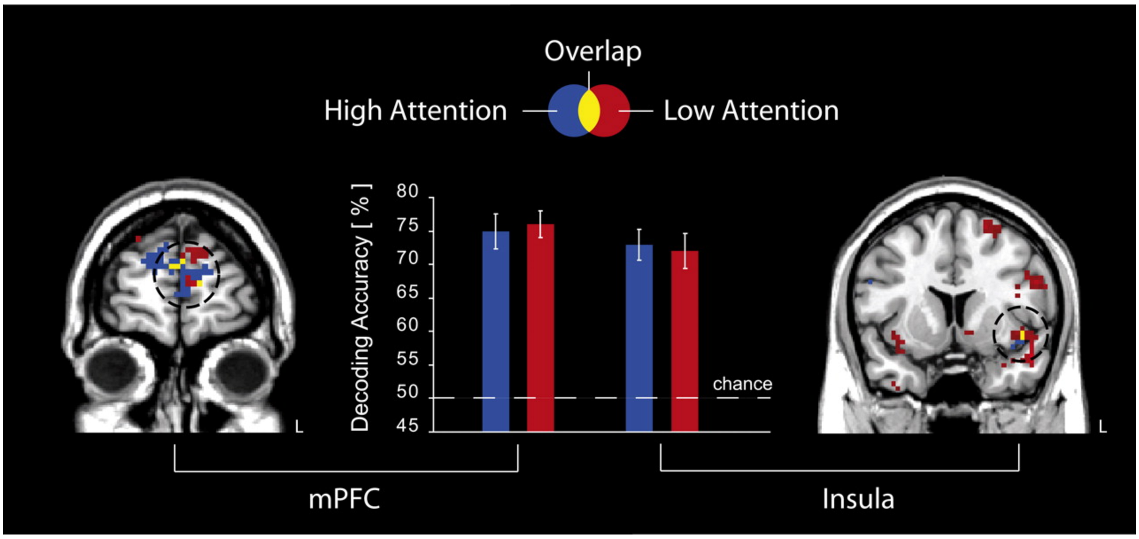

Figure 10: fMRI results from the two groups being analysed. The hight attention group is in blue and, in red, the low attention group. Their choices could be predicted with high accuracy, much higher than by chance, by analysing the prefrontal cortex (left-hand side) and insula (right-hand side) responses to exposure to the different cars, even in the group that was not aware they had to make a choice and was being actively distracted from evaluating the cars (Tusche et al., 2010).

Neural activity can even be used to predict hypothetical choices when people are not engaged in decision making (when, for instance, only imagining a situation), as shown by Smith et al. (2014). This can be used to predict choices in new and not observed situations (*e.g.*, for a new product or when a new policy is enforced), where there is lack of data and surveys of preference / intent typically yield biased results. We also know that when dealing with people we can be instantly affected by their looks or gestures, creating an image that was not formed from a deliberate rational process. We are indeed, influenced, or even guided, by automatic processes within our brains.

The realisation that our decisions deviate from expected models and lead to errors motivated research on the failures of human nature (§3.3). In contrast, others were motivated by surprising success cases where human judgment was particularly effective (§3.4).

3.3 A tale of two brains

We have introduced the question of conscious choice that may affect how decisions are made. We need now to further explore how the human brain operates.

It has long been recognised the existence of two different processes when it comes to cognition (see for *e.g.*, Evans, 2008, for a review). This duality attempts to explain why humans deviate from the theoretical models of decision making and rational judgment and we will use the terminology proposed by Stanovich and West (2000) of *System 1* and *System 2*.

System 1 is always active and not under our control. Therefore it is fast in giving us its perceptions of what we are encountering or solutions to problems. It can do it without requiring much effort and for this it uses heuristics. It usually does a good job at understanding our environment and making short term predictions, even of complicated events. Think of a football player who can guess where the ball is going to fall and which speed they must achieve to catch the ball without actually having to solve the equations of movement. But now the reader may be remembering what was mentioned in §3.1, how easily it can also be fooled by simple illusions and better understand its consequences when allied to such an impulsive system. System 1 is also affected by systematic errors, biases, which we will explore better in §3.3.2.

System 2 is more rational. We know that often first impressions are wrong (even though it is very difficult not to be influenced by them) and System 2 can be used to check the work of System 1. It is also engaged to solve more complex problems when we cannot reach a quick answer. Table 2 shows a comparison between the two.

The two systems work together to minimise effort while optimising outcomes. Since System 1 is always on, it will take the lead. System 2 will only be engaged if the problem is difficult or the answers provided by System 1 cause any suspicion. We like easy to under-

Table 2: Comparison between System 1 and System 2 characteristics.

System 1	System 2
Unconscious	Conscious
Effortless	Effortful
Automatic	Needs to be called
Always on	Not always used
Often wrong	Fooled by System 1
Heuristics	Rational

stand, simple, obvious and familiar things, but these may not be the correct answers and yet, we are fooled into accepting them as valid. It may also happen that the two systems enter a conflict. An example are illusions, such as we have seen, where even knowing the reality does not allow us to see it or the Stroop effect (Stroop, 1935) in Figure 11 (although with previous works already about it (MacLeod, 1991)) in which the automatic simple process of reading a word conflicts with the effort of retrieving its colour. Sometimes this example is shown with a reference to right and left brain, but that is incorrect. Not only tasks are not clearly divided between hemispheres, but also the simplistic connection between hemispheres and personality (creative, artistic, emotional *vs.* rational, analytical) is not there (Jarrett, 2012). And, in this particular case, neural imaging has also shown that the parts of the brain activated by this task are not divided between left and right (Milham, 2003).

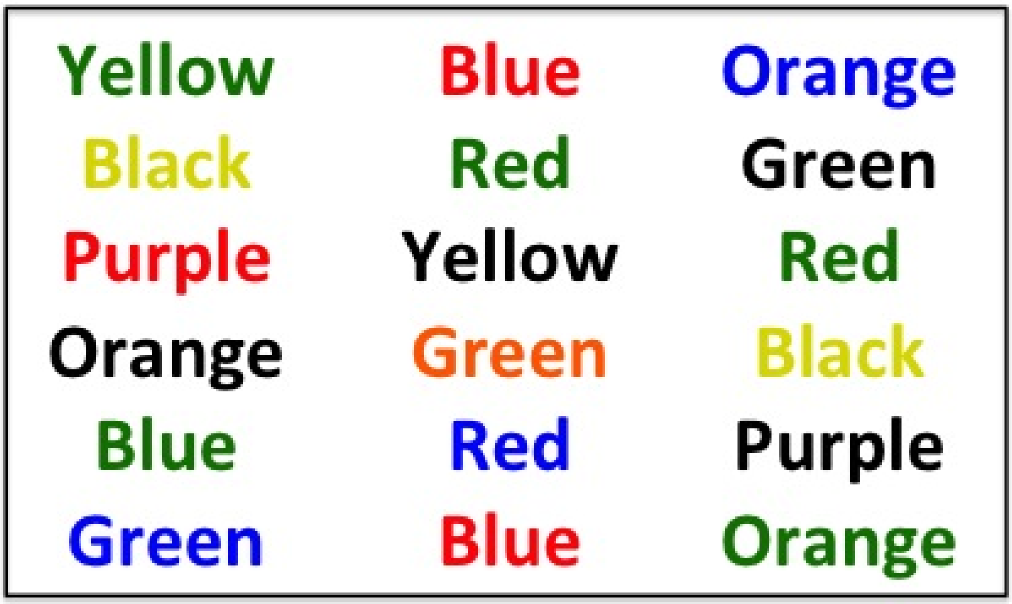

Figure 11: The Stroop effect demonstrates the conflict between the automatic simple process of reading a word and the effort of retrieving its colour when the reader tries to say the colour of the words in the picture. This task is also slower and causes more errors than reading the words.

System 2 is lazy, attempts at conserving energy and when engaged in effortful thinking, it diminishes attention to other things. An example the reader may know is the video produced in 2008 by Transport for London as part of a safety campaign that became widely popular[4]. In it, the viewers are asked to count how many ball passes are made by a team, but very often fail to notice a person in a bear costume moonwalking across the screen.

How can we force ourselves to engage System 2? Sometimes this happens involuntarily, such as when someone is thinking in a foreign language. Hayakawa et al. (2016) noticed that this affects choice by reducing emotional attachment and deliberation. It distances decision makers from the decisions being taken, reducing mental imagery (Hayakawa and Keysar, 2018) and the grasp of System 1. It, therefore, leads us to make less biased decisions (Keysar et al., 2012) and changes how we weigh costs and benefits. But the largest behavioural changes were detected in the moral domain - foreign language induces utilitarianism. It may not be realistic to shift language, but we may embrace it more instead of shying away from discussions that are not done in our mother tongue. Companies can also gain from having international workforce or dealing in international settings and should not be tempted to translate everything into their home country's language. Pay attention to the ideas and input of workers speaking in a what is a foreign language to them. We should also be critical of information we receive or logical steps we take and evaluate them without instantly accepting them as valid.

3.3.1 No, you cannot multitask

> *There is time enough for everything in the course of the day, if you do but one thing at once, but there is not time enough in the year, if you will do two things at a time.* - Lord Chesterfield

Our cognitive limitations also extend to multitasking, a myth that should not be perpetuated and is still very present in business world. This impacts how people perceive their own work and abilities, how they manage time, how they learn or what kind of skills are asked for in job adverts. It makes us more susceptible to the cognitive shortcomings be-

[4]This video, Moonwalking bear, and others can be seen at `https://www.awarenesstest.co.uk/`

ing discussed in this work. In reality, we cannot perform two tasks simultaneously and what happens is a rapid switch between tasks. When we are exposed to multiple stimuli, we face a bottleneck while the brain is determining which task to perform first (Tombu et al., 2011), due to its limited processing power. Even when voluntarily switching tasks, it takes us several minutes to recover from what the brain sees as a distraction and can be something we consider simple such as answering an email or a phone call (Mark et al., 2008), leading to increased stress, frustration and time pressures. The lost time with task-switching can cost up to 40% of our productivity (Weinschenk, 2012) and this should not be a surprise. We know that switching service providers, suppliers, processes, *etc.* has costs, so why should not there be any for mental tasks? And it is not just an overload caused by cognitive tasks, it can also happen when combining physical tasks, as simple as walking and talking or thinking. Hyman et al. (2009) reported that people bump more often against others when walking while talking on the phone and Kahneman (2011) noticed a slowing down of walking pace during more effortful mental exercises. Foerde et al. (2006) have also found that multitasking adversely affects the way we learn, making it more difficult to retrieve information and apply it to new situations.

Media multitasking, in particular, is becoming very relevant nowadays, with increasing digitalisation and connectivity in our lives and at the workplace. People engaged with the consumption of more than one item of content at the same time, such as browsers, shared workspaces, internal communication applications (from the traditional email to chats like Yammer), Skype, multiple windows, phones, social media presence, *etc.* Ophir et al. (2009) compared light and heavy media multitaskers and found that heavy multitaskers were more easily distracted, had worse memory, and performed worse at task switching, being more affected by irrelevant information or tasks. It is unclear if people with inability to concentrate become multitaskers, or if the multitasking activities are damaging their cognitive performances.

3.3.2 Heuristics, biases and fallacies

You can't connect the dots looking forward. You can only connect them looking back-wards. So you have to trust they will somehow connect in your future. - Steve Jobs

We have seen that not only people are limited in their ability to gather and process information and in the available time to perform decisions, but also that engaging System 2 has mental costs. This leads us to use *heuristics*, simple rules people use when making decisions. They act as shortcuts that save time and effort and usually lead to good enough results. But they can also lead to systematic deviations from rationality. We call these deviations biases. Let us explore some examples of the relevant heuristics than can affect the decision-making process.

Substitution

When a question is too difficult to evaluate, we often replace it for another to which we can answer. While this can be a valid purposeful strategy, the substitution can also be done automatically and without us noticing what is really happening. It is this second case that is considered a heuristic and which can lead to problems. For example, when deciding how much should be donated to help an endangered animal, most people replace that question by how much they like the animal and then match that intensity with a monetary value. This leads to uglier animals receiving fewer donations than cuter ones, independently of their threat status or importance to the ecosystem (Hunt, 2016).

Affect

The Affect heuristic is a quick and automated response from System 1 to a certain stimulus that draws a response from the good or bad feelings experienced in relation to that stimulus. This is why messages that create emotions are more persuasive than purely factual ones (Keller et al., 2006).

Availability

When using the Availability heuristic, people assess the probability of an event by the easiness they can recall similar events. While generally things that occur more frequently are easier to remember, we have already seen how our memory fails us. We also give more importance to events close to us or to those that are more unusual. And we are influenced by the reporting of events and repetition. While factors such as consistency and extremity increase confidence on a prediction, they are often negatively correlated with accuracy (Kahneman and Tversky, 1973). For instance, successful stories of startups are much more common than failures, but we know that only a minority of startups succeeds.

Representativeness

In Representativeness, we assess how likely it is that *A*, where *A* can be an object, process, event, *etc.*, belongs to a certain class, *B*, by assessing to which extent *A* resembles *B*. But by doing so we ignore *B*'s base rate. It also leads us to extrapolate that *A* will have other characteristics that are typical of *B*. As an illustration, it has been noticed that investors see a good company as a good investment, but even though a good company may have strong earnings, good management, growth, *etc.*, a good investment means a company whose share price increases more than other shares (Solt and Statman, 1989).

Anchoring

Anchoring involves starting from an available value, the anchor, and then adjusting it towards what they feel to be a correct answer. The anchor can come from a similar example or the wording of the problem being solved. What often happens is that the adjustment is insufficient and starting at different anchor points leads to different solutions (Tversky and Kahneman, 1974). We see it commonly in negotiations or consumer choices.

Biases are systematic errors that influence judgment. There are many such unconscious limitations[5], but Benson (2016) has aggregated them into four main domains, summarised in Figure 12, based on what leads to the bias, excess information, lack of meaning, time constraints, or lack of memory. Biases make our life easier and are mostly used by System 1 although they can also affect System 2 and we are definitely influenced by them, which interferes with decision making processes that are expected to be rational choices. Furthermore, there is no connection between biases and degree of confidence, their effects do not lead us to doubt and we can feel very confident about a biased conclusion. We distinguish these biases from those brought on by motivational effects, where someone who is biased leans towards a particular position because it is favourable, not because of cognitive mechanisms.

[5]For a very extensive list see, for instance, `https://cdn-images-1.medium.com/max/2000/1*71TzKnr7bzXU_l_pU6DCNA.jpeg`

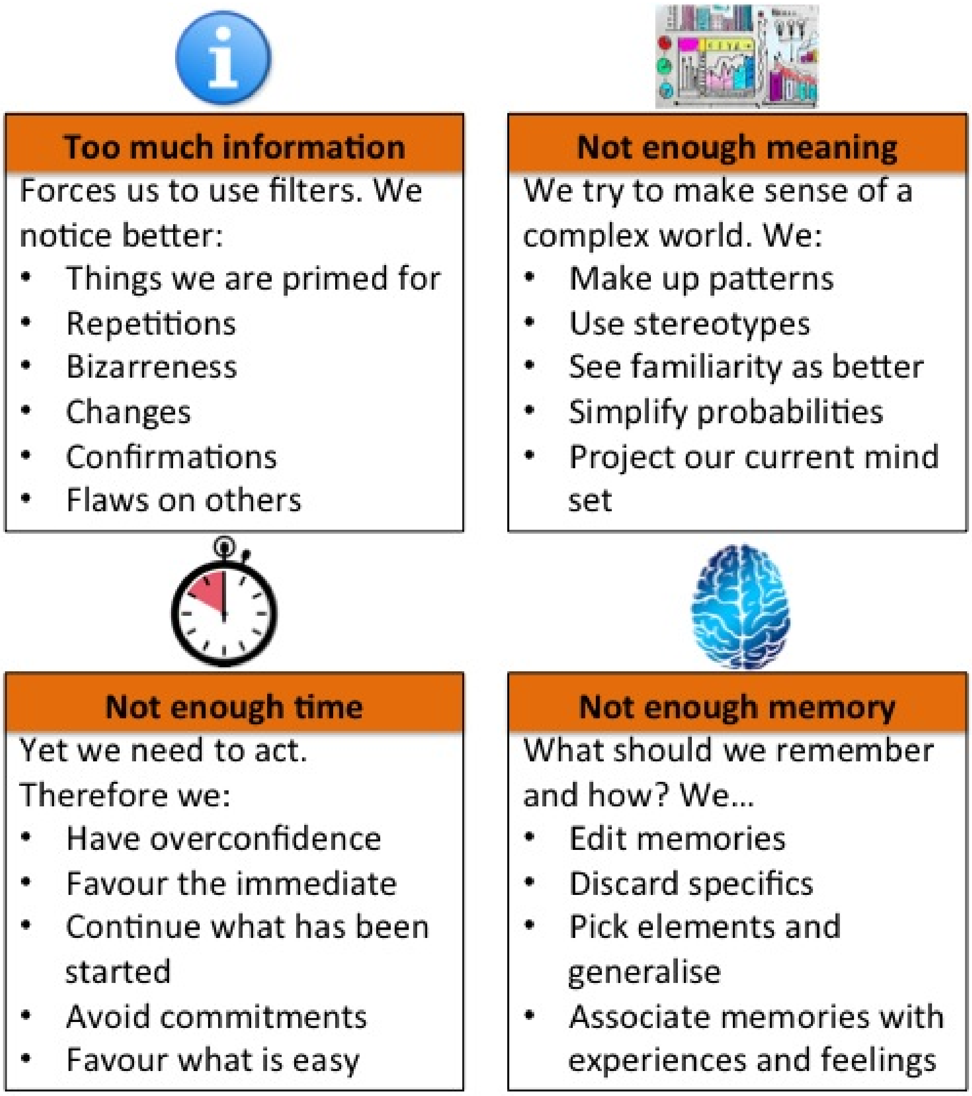

Figure 12: Four types of constraints that lead to most of the biases we experience. We can see how these relate to Simon's bounded rationality (§ 3.2).

We will explore some common biases that can have great impact on decision making and business life.

Einstellung effect

This is the tendency to stick with a familiar solution to a problem and ignore alternatives that can even be better. It is particularly relevant in a constantly changing world or when people move from one company to another (or even between industries) and attempt to apply similar processes. In a famous example, Luchins (1942) gave participants three water jugs with which to extract a certain volume. After learning the rule, participants continued to use the same sequence to reach other quantities, while ignoring simpler solutions.

– Take a break and let your mind wander. Try to think as a beginner. Enlist the help of a different person with a fresh view on the problem. Diversity helps.

Linear

Many things in our world obey linear relationships (quantity of objects and the space they take or their total cost, time-distance-velocity, *etc.*) and we have evolved to intuitively understand them, but we struggle to understand non-linear relationships and fail when applying the same kind of thinking. For example, profits are dependent on costs, price and sales volume. Often companies get excited by forecasts of increased sales if they lower prices, but fail to recognize the necessary volume increase necessary to keep profits. Non-linearity can also be seen between attitudes and behaviour, where only the most extreme beliefs impact behaviour (van Doorn et al., 2007).

– Learn to detect non-linearity. Focus on outcomes, not indicators.

Salience

People are more likely to focus on objects, events or information that are more prominent and ignore those that are less so. This creates a bias in favour of things that are striking and perceptible (Kahneman et al., 1982). That is why people are more afraid of flying than driving even though the chances of injury / death in a car accident are much higher (for example, data on the USA by Savage, 2013). Businesses often run into planning errors and delays because of a failure to account for less salient aspects of the process such as administrative tasks or other ancillary steps (Hirshleifer, 2008).

– Let the numbers speak for themselves and look at statistics instead of relying on your memory.

Overconfidence

What a Man wishes, he will also believe. - Demosthenes

Overconfidence happens when an individual's confidence in their judgment is higher than what should be expected from an objective reasoning or for which there is supporting evidence. According to Moore and Healey (2008), it can be divided into overestimation, overplacement and overprecision. But, both society and companies do not see uncertainty and doubt in good light. Confidence is valued, even if faked.

– Focus on probabilities. Think of what can go wrong.

Hindsight

This is the tendency to wrongly believe, after the results are known, that we had correctly predicted them. It originates from our selective memory (§ 3.1), a re-evaluation of likelihood of events and the desire to prevent emotional discomfort by believing we live in a predictable world (Roese and Vohs, 2012). It diminishes our ability to learn from past events, lets us think we are better predictors than we are and can make us falsely confident. This bias causes people to see past results as appearing more probable than they did initially. It can give the "I knew it all along" feeling and it can also make analysing past errors more difficult. If it seems "obvious" now that a certain action would lead to a certain reaction, then why did the person do it? What seems obvious looking back was not obvious at all at the time and one needs to understand why the actions made sense then.

– Document your predictions so that later you can check what you really knew. Do not revise the odds of an event based on the results of a single case.

Confirmation

This represents a case of selective perception where we seek out information that reaffirms our beliefs or hypotheses and we discount information that contradicts them, a form of "cherry-picking" evidence. There is also a tendency to interpret ambiguous evidence as if it supports our case. It was first reported by Wason (1960) in what was one of the first researches into cognitive biases and deviations from rationality.

– Seek out disconfirming evidence.

Halo effect

This term was coined by Thorndike (1920) after realising that certain characteristics of people were rated in ways that correlated more than expected if they had been independently analysed. It appeared that they were all influenced by a general feeling, a "halo". This halo effect happens when one trait of a person or thing (for example, websites, Lindgaard and Dudek, 2002) serves as the basis for a global judgment of that person or thing. It supports rapid decisions, even if biased ones and can work in both the positive and negative directions.

– Examine the evidence objectively and independently and try to avoid confirmation bias. Do not pre-judge people / things.

"What you see is all there is"

It is not, but often it might as well be. *What you see is all there is* (Kahneman, 2011) means is that we are quick to jump to conclusions based on limited data. We make judgments and form impressions based on information we have and as long as System 1 creates a coherent story, we do not stop to think about the information we do not have.

– Ask first what is the information needed to address the problem instead of quickly taking only what is available.

Dunning-Kruger effect

> *Ignorance more frequently begets confidence than does knowledge.* - Darwin

> *The greatest enemy of knowledge is not ignorance, it is the illusion of knowledge.* - Stephen Hawking

The Dunning-Kruger effect is a bias in which unskilled people overestimate their abilities (Kruger and Dunning, 1999). Not only these people lack competence, they also lack the ability to recognise their incompetence. This directly affects the subjective confidence that plays a critical role in decision making (Figure 13). People make most decisions on the basis of subjective measures of certainty, based on their feelings of confidence.

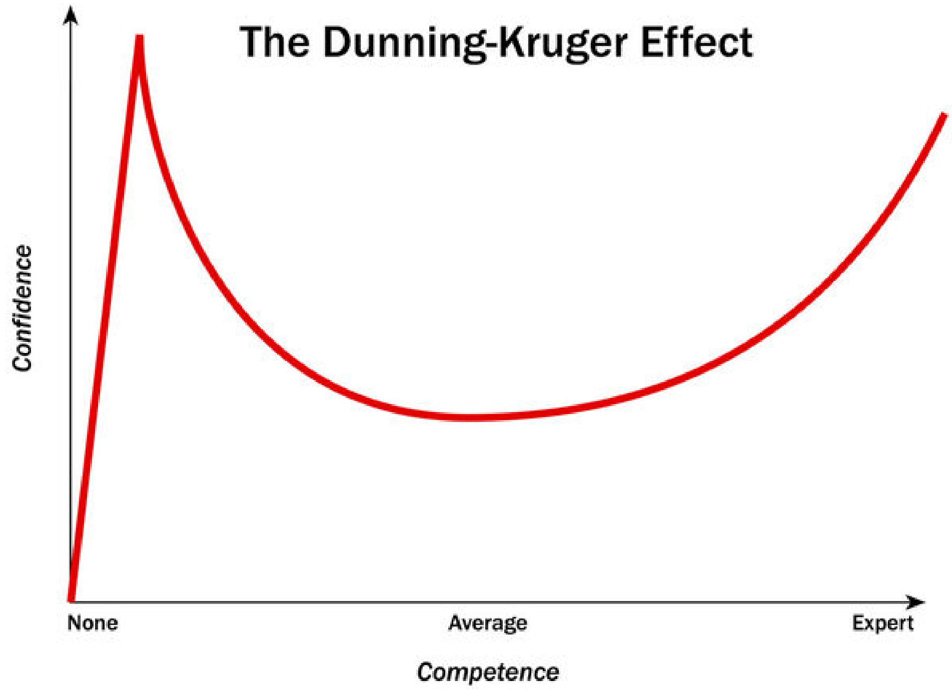

Figure 13: This graph (Poundstone, 2017) shows how confidence changes with competence and highlights the Dunning-Kruger effect. People who have gained just a bit of knowledge on a subject exhibit very high confidence on their skills, unable to correctly assess their expertise. Confidence falls once people gain enough knowledge to evaluate themselves and better understand the difficulties of the subject. It can even drop more than what it would be accurate, especially for those who are surrounded by experts, leading to impostor syndrome. Confidence more accurately matches skill level for experts.

While unskilled people have more confidence than they should, often people with some expertise will feel insecure and underestimate their knowledge, leading to *impostor syndrome* (Clance and Imes, 1978). Highly skilled individuals may have difficulties understanding other people's struggles because they underestimate their relative competence and wrongly assume that tasks which are easy for them are also easy for others. The work from Kruger and Dunning also highlight the problem with feedback and learning that not always produce the expected results.

Since the skills required for competence are the same as the skills required to recognise competence in themselves and in others, the Dunning-Kruger effect appears, for example in hiring. Unskilled candidates come across as very confident and blissfully self-assured, which, combined with halo effect, impresses recruiters. In this digital age, with easy access to information, we also see an abundance of so-called experts who have learned by themselves and distrust those with proven expertise in the field. This is not, of course, a defence of arguments from authority, which are fallacies.

– Always keep learning. Be aware when you are entering a new domain and assume you do not understand the problem, applying critical thinking and the scientific method to solving the problem. Subjective judgment and subjective confidence are not safe indicators of success. Help others understand the level of their competence.

One other aspect that can be connected to heuristics and biases are *fallacies*, faulty reasoning in the construction of an argument that can be used to support decisions. These should, however, be easier to detect as they are not subconscious processes that trick us, they come from poor preparation and understanding of reasoning or done deliberately. We can divide fallacies into (a) emotional, (b) ethical, and (c) logical. Without denying the importance of emotional and ethical fallacies, the logical ones fall more in line with the purpose of this work, which justifies presenting some notable examples relevant in the business world: *sunken cost*, where past expenditures are taken into account when deliberating about future investments; *planning*, in which predictions about how much time will be needed to complete a task suffer from optimism bias and underestimate the time needed; *assuming cause / effect*, when *A* precedes *B*, it is assumed that *A* caused *B*; generated by similar principals as *misunderstanding of correlation and causation*, by which correlation between two variables is used as an indication that one causes the other. Lunsford and Ruszkiewicz (2004) present an in-depth discussion on the topic.

3.3.3 Emotions and moods

> *In order to have anything like a complete theory of human rationality, we have to understand what role emotion plays in it.* - Herbert Simon

Until now, we have been looking mainly at cognitive processes. But we know that emotions are a pervasive part of the human condition and we have already seen that they influence decision making in ways that are not modelled by the rational being paradigm. Recognition of this fact has gathered increasing attention since the late 1990s / early

2000s (Figure 14) and a wealth of research is being developed in an attempt to understand what many psychologists believe is a dominant driver of decision making (Lerner et al., 2015, and references within). Emotions guide us towards avoiding negative feelings and increasing positive ones, maximising what Kahneman (2011) calls *experienced utility*.

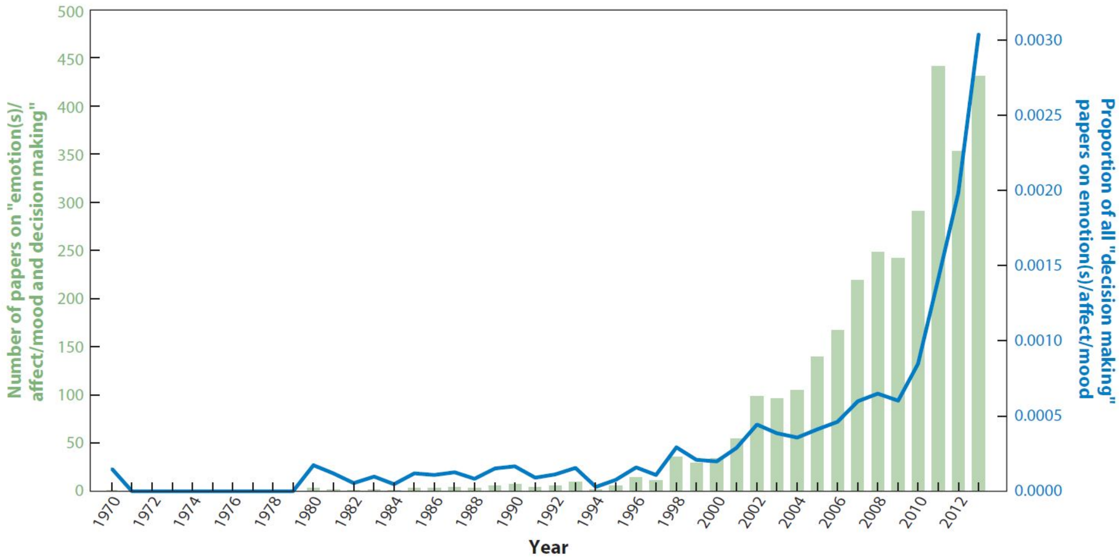

Figure 14: This Figure by Lerner et al. (2015) shows the recognition of the importance that emotions have in the decision-making process. The green bars show the growing numbers of scientific papers on the topic and the blue line shows their proportion when compared to all decision making papers.

Emotions are intense feelings directed at something or someone, caused by specific events and usually short in duration. There are a variety of terms used to describe them and, being subjective experiences, they can be difficult to define, but Cowen and Keltner (2017) report the existence of 27 main categories. Moods, on the other hand, often lack a contextual stimulus, last longer and are less specific (usually just a general good or bad mood). One should note that emotions can turn into moods and moods can affect emotional responses.

Some of the heuristics and biases described earlier are connected to emotions. For example, when studying the confirmation bias, Wason (1960) reported that some participants of his experiment had been "unable, or unwilling to test their hypotheses". This unwillingness can stem from an attempt to avoid the disappointment of hearing even an inconsequential "no" and desire to pursue more gratifying positive responses, even if they led to a wrong conclusion[6]. In addition, the affect heuristic may lead people to focus on confirming a belief[7] because they are not comfortable with the costs (even if emotional) of being wrong and emotionally charged issues lead to stronger confirmation bias. The results at organisational level are, development of a "yes man" culture, overconfidence and lack of risk-mitigating strategies.

Due to the important part that emotions take in our lives, there has also been an incentive to improve the skill of *emotional intelligence*, the ability to identify and manage our own emotions as well as of others. This is important not only to understand decisions, but also to work in a collaborative environment, for leading and being led, and for interacting with customers or suppliers.

3.3.3.1 Embodied mind

We have seen that emotions influence decisions and are mostly seen as disrupting reasoning. Damásio (1994) argues that in spite of this, emotions are also necessary for reasoning. Indeed, reasoning and emotions share certain structures of the brain and people without some parts of the brain that affect emotions are also unable to make certain choices. The mind, that we have been discussing thus far, is connected to a physical brain. And this brain is, in turn, connected to the whole body - the embodied mind - both receiving and sending signals.

This means that not only emotions influence decisions, but also states of the whole body can influence processes of the brain. And we have seen evidence of this. Xu et al. (2015) showed that people buy more when they are hungry; Danziger et al. (2011) showed that judges issue harsher sentences when hungry, although there are other possible explanations for it, from tiredness to time constraints or even a statistical artefact; Tuk et al. (2011) report that people with increased bladder pressure display increased ability to resist monetary impulsive choices; Soars (2009) reviews existing literature exploring the relationship between senses and buying behaviour; and pleasant fragrances are even linked to higher positive affect and better prosocial behaviour (Baron, 1997); *etc.*

[6] An adapted version of Wason's experiment can be done interactively at https://www.nytimes.com/interactive/2015/07/03/upshot/a-quick-puzzle-to-test-your-problem-solving.html

[7] Section 3.3.4 will expand more on beliefs.

In addition to these body states, Damásio (1994) argues that when facing a decision, we evaluate possible outcomes and these generate body reactions, "gut feelings", that mark each possibility in a much faster way than the rational cost / benefit analysis and have the tendency to warn us about bad outcomes. The brain then analyses the emotional salience of these *somatic markers* to decide among the possible alternatives. Our journey has taken us from a rational mind, through an emotional mind that is now connected to a physical body, all influencing us when making decisions.

3.3.3.2 Group dynamics

Emotions are particularly important when looking at groups, since they affect people's interactions. Group discussions and decision processes are not only impacted by the shortcomings of the human mind, but also by relationships and emotional changes and responses driven by the group dynamics.

Most teams follow a certain path when forming and working together, described by Tuckman (1965), with four initial stages - *forming, storming, norming, performing* - to which later was added *adjourning* (Tuckman and Jensen, 1977). They evolve from an initial desire for acceptance and search of guidance and leadership to the rise of conflicts when different personalities start clashing until the group members eventually learn to work together and trust each other's work. By then the group becomes more united, personal relationships grow and performance is enhanced. It will eventually come to an end, which can be another emotionally significant period. These phases modulate the group interactions and we can see how important emotions are in the process, but at each stage people are under the influence of the other mechanisms discussed in this work. And because there is a constant interaction, emotional responses can constantly change and drive decisions.

Group members can fall prey of the *transparency fallacy* and think they understand each other better than they actually do, leading to miscommunication problems. In addition to affecting individuals, *confirmation bias* can also affect groups and lead to *groupthink* (Janis, 1972). The group will favour reaching consensus and will discard alternative views. Janis describes groupthink as deriving from three causes, overestimations, closedmindedness and pressures toward uniformity. While, groupthink is controversial, it explains empirically observed problems in collective decision making. The *stereotyping heuristic* can also lead to ideas from members discussing matters outside their perceived stereotype (usually connected to their roles) to be discarded or even people disengaging from discussions they think are not their responsibility. And when conflicts arise, the *Einstellung effect* can make resolution harder because people stay attached to previous ideas that are not working.

Groups should have clear goals and rules and understand that conflict and disagreement are not only natural, but should be welcomed if the group is to learn. Communication is of the utmost importance and this means both actively participating and actively listening to the other members. For group decision making, it is crucial to obtain information from each member in an independent way so as to prevent some members from influencing others as it can lead to confirmation bias or members shying away from discussion to avoid confrontation, in particular if there is hierarchy involved.

3.3.4 When beliefs encounter reality

Everyone is entitled to his own opinion, but not to his own facts. - Daniel Patrick Moynihan

Our thought process is related to our internal model of the world, how we make sense of things, which provides us with a cognitive foundation and emotional security. Quine and Ulian (1970) depict it as a *web*, where the nodes hold our beliefs and the connections represent the relations between them. At the centre lie deep-seated beliefs, the ones more fundamental to our view of the world. Surrounding them are inferred beliefs and observations and experiences lie at the surface, interacting primarily with these inferred beliefs[8].

We often experience something that contradicts our beliefs, a *dissonance*, and leads us to revise them. It is easier to change those beliefs that lie closer to the periphery than

[8] There are other models of how we organise our worldview (*e.g.*, Hiebert, 1985). It is also conceptualised in a structured manner with layers, more central issues and other more superficial. The implications to what we discuss are similar.

the deeper ones. More fundamental beliefs are more interconnected and changing them could affect so much of our worldview that we find that unacceptable. This is important to understand what guides us, how we perceive and evaluate evidence and how we incorporate or discard it.

Festinger (1957) explores this cognitive dissonance and the steps we take to restore internal psychological consistency in order to function in the real world. The process is the following:

- We are sensitive to inconsistencies between beliefs and actions or observations.
- These inconsistencies will cause a dissonance, which is uncomfortable, and prompt us to resolve it.
- Resolution can be done in one of three ways:
  - Change beliefs
  - Change actions
  - Change perceptions of actions or observations

Decision making involves choices. These lead to opportunity costs. We lose the advantages of not chosen alternatives while, at the same time, are forced to accept the disadvantages of the chosen one. Brehm (1956) found that we change perceptions by artificially increasing the attractiveness of the chosen alternative and decreasing the attractiveness of the rejected ones, what is known as spreading apart the alternatives. We may also engage in confirmation bias, searching for evidence that supports our beliefs, while ignoring or altering what contradicts it. This helps to explain our tendency to rationalise.

Although the concept is understandable and we can see evidence of it, it is somewhat subjective. We cannot physically observe cognitive dissonance and, hence, cannot measure it.

3.3.5 Normalisation of deviance and complacency

Series of suboptimal decisions can lead to shifts in established processes. These can be conscious actions, but very frequently a consequence of human nature and the unnoticed aspects that affect our decision making. The theory of normalisation of deviance was developed by Diane Vaughn when researching the causes for conflicts, mistakes, and disasters and became more widely known to the public when a book investigating the decision-making process that led to the Challenger Space Shuttle accident was published (Vaughan, 1997). Normalisation of deviance happens when people within the organisation become so accustomed to a deviation that they do not consider it as deviant, it becomes the new norm. From that new norm, new deviations will occur, shifting practices closer to riskier situations without it being noticed (Figure 15).

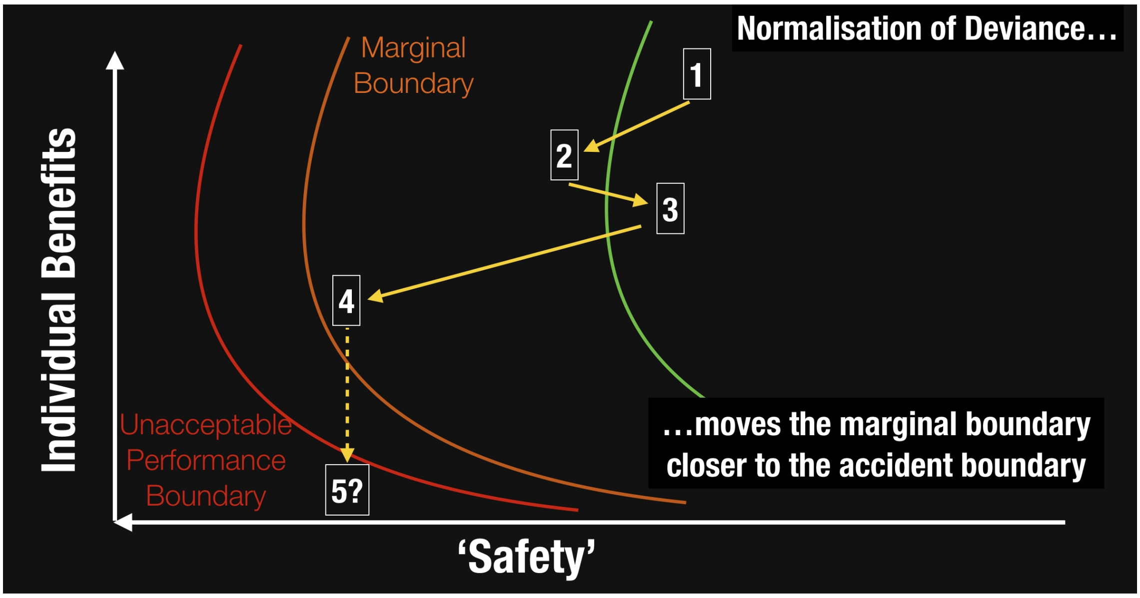

Figure 15: This Figure (Lock, 2016) attempts to illustrate how deviances become the new norm and how that moves us closer to danger. Processes are sometimes set up in ways that we perceive not to be efficient or practical. It may happen by accident or on purpose that we deviate from them (2) and nothing bad happens. We come back to safe practices (3), but eventually cross the safe boundary again and become accustomed to it, nor realising that our new normal state (marginal boundary) is now much closer to that of unacceptable performance. If new deviations occur, it will be likely that at any moment one will lead to a major problem (5).

There are several tragic examples to illustrate this phenomenon. The Challenger Space Shuttle disaster (1986) was caused by a series of decision stages that approved a launch that should not have been approved. Later, with the Space Shuttle Columbia (2003), insulating foam broke away, an event that had happened before, but was seen as a maintenance problem and not a risk factor. This time, however, it damaged the heat protective shield and the shuttle burned during entry. With the cruise ship Costa Concordia (2012), the captain deviated from the approved route and ran aground. Also the Proteus Airlines

Flight 706 (1998) deviated from route, changing from instrument flight rules to visual flight rules and collided in the air with another aircraft which had a turned off transponder, which was optional at the time. These were things that had been considered within acceptable risk even after processes had deviated from their original form, until the moment they were not and only an accident led to moving the practices to safe parameters again. The mentioned examples are the most extreme, but deviations from processes happen in many instances, leading to bad results. Elon Musk believed that inefficient processes had led the space industry to evolve slowly, without much innovation and being too expensive. His vision for SpaceX[9] was to take advantage of these inefficiencies (Vance, 2017, p. 114). Overall, aviation (Albright, 2017) and health care (Banja, 2010) have perhaps been the industries more engaged with researching this problem.

Normalisation of deviance is easier to prevent than to correct. Organisations have to combat ignorance concerning the issue and have clear standards to be followed. Improved situational awareness (Fig. 2) and communication is extremely important and so is a team culture where people are encouraged to speak up and where failures (personal or from the system) can be discussed, a *just culture*. We need to recognise that equipment and processes are developed by fallible people and be proactive when things do not look right.

3.3.6 Noise

> *My soul is a hidden orchestra; I know not what instruments, what fiddlestrings and harps, drums and tamboura I sound and clash inside myself.* - Fernando Pessoa

When looking at deviations from what would be optimal decisions, biases have usually drawn more attention. But, as we have seen, there are more influencing factors and all together they can create *noise*. While biases tend to shift decisions in a determined way, noise has a more random variability and leads to inconsistent decision making. Differences between bias and noise are illustrated in Figure 16.

This inconsistency has been noticed in several situations where repetitive evaluations of the same parameter yielded different results. It was identified, at personal level, in medical

[9] `http://www.spacex.com/`

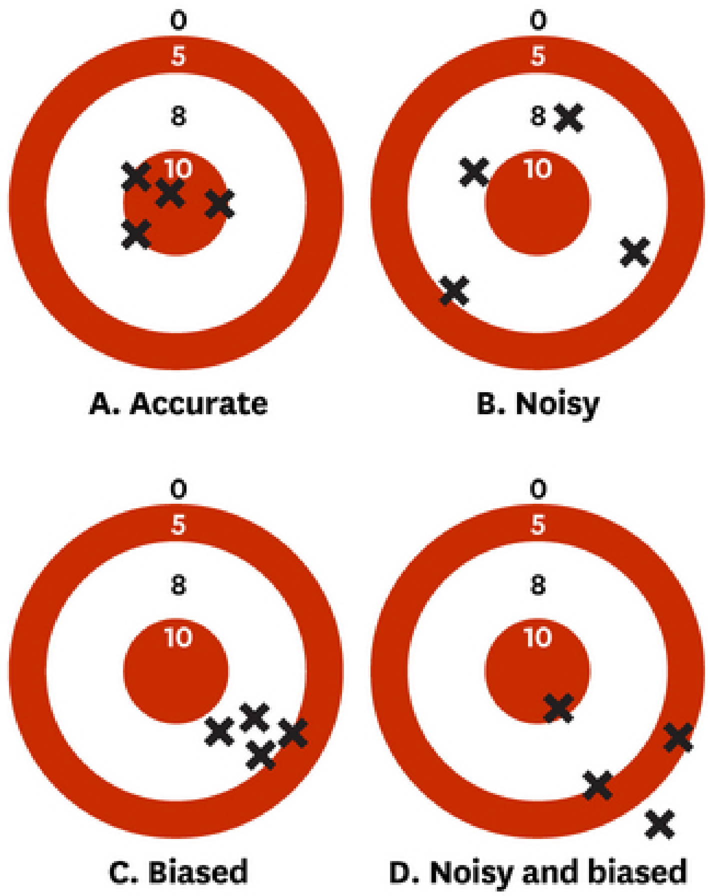

Figure 16: In this Figure (Kahneman et al., 2016), we can see the different behaviours of biased and noisy decisions. When compared to an ideally accurate decision (A), noise creates scatter (B) and biases create a shift in the same direction (C). If both are present (D), the results will be both deviated and scattered. We could still differentiate between the effects of bias and noise even if the targets were removed from the image.

diagnoses (Einhorn, 1974), ratings from wine experts (Gawel and Godden, 2008), stock valuations (Paul, 1969), real estate appraisals (Adair et al., 1996), and many other cases. At organisational level in, for example, insurance underwriters (Matias, 2017).

Judgement implies the existence of noise. It can be present in the data, introduced by our senses, in our neurones, perception, internal judgment, emotional state, *etc.* At different instances we can even be paying attention to different things and weighing them differently.

For an organisation, differences between people can also be considered noise, especially when people are addressing similar issues. While these should lead to similar outcomes, in reality they are dealt with in different ways. This causes the organisational decision making to be inconsistent.

Noise can be detected and measured even without knowing where the target (the optimal decision) is, by evaluating the spread of evaluations that should be similar. Removing the targets from Fig. 16 would still reveal a scatter when noise is present. This noise can be reduced by the use of algorithms[10] A meta-study by Grove et al. (2000) shows comparisons in a variety of fields between statistical (algorithmic) prediction techniques and formal (human) ones, where the former consistently outperformed the latter.

3.4 Naturalistic decision making

In the previous sections we have been focused on exploring how people deviate from rational thinking, how classical models of decision making are not adequate to reality and the types of problems that can originate from our human condition. It should also be noted that, most of the time, we fair quite well in spite of our limitations. In this section we go one step further and look at situations where people actually excel at decisions that do not appear to be supported by explicit evidence and following a formal evaluation process.

Naturalistic Decision Making (NDM), started to be researched in the late 1980s. By then, it was evident that people used heuristics and biases in their decision making, but the process was still being evaluated and compared to the formal standards that were looking for optimal decisions in well defined and controlled settings. Not only these were not realistic, but they could even be impractical in real settings (Yates et al., 2003). Instead of looking at how people fail, NDM comes from the opposite direction. It acknowledges that people are often in difficult and uncertain conditions (something we had already recognised in § 2 when mentioning VUCA) and with limited resources. It then explores how people make decisions in those situations and are effective.

There are several models that attempt to explain decision making in more realistic terms. Hammond et al. (1987) posit that our decisions lie in a continuum that ranges from *analytical* to *intuitive* and decisions are a mix of elements from both sides, with varying weights. Rasmussen (1983) classifies behaviour as being *skill-based, rule-based*, or *knowledge-*

[10] An algorithm is a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer, either through traditional programming or machine learning.

based, moving from more automated actions to conscious actions in unfamiliar environments. It is particularly important in the fields of human factors, safety science, human error and accident research, especially when there is a human - machine interaction. Klein (1989) developed the *Recognition-primed decision* model (RPD), which lies at the intuitive end of Hammond et al.'s scale and, since it explains the processes in different phases of a decision situation, it will be described in further detail. In general, the different models are in agreement when it comes to recognising that people use prior experience to categorise decision situations and that they use these categories to suggest appropriate courses of action.

3.4.1 Recognition-primed decision making

The Recognition-primed decision process (Klein, 1989), illustrated in Figure 17, is based on three steps that we follow even if unconsciously and quickly: 1. Experiencing the situation; 2. Analysing the situation (Is it similar to a previous one? Do we need more information? How would possible scenarios play out?); 3. Implementing the decision. Step 2 is critical as it depends heavily on the expertise of the decision maker, which comes from *tacit knowledge* (Klein and Hoffman, 1992) derived from experience. It is experience that allows people to pick up relevant cues, visualise how the situation should develop, recognise if something is missing and go through mental simulations of possible actions. Unlike formal choice processes discussed previously where people are expected to chose the best of several possibilities in a rational way, reality very often leads us to chose the first option that appears to work. It is consistent with Simon's idea of satisficing. The insight that experts can derive from a situation comes from observing a *contradiction*, a *connection* or being at an *impasse* (Klein and Jarosz, 2011).

Some danger signs should be noticed from Fig. 17. One might assume a situation is familiar due to scarce evidence, when it is in fact a different one or when contexts may have changed. If extra information is needed, perhaps the best course of action is to exit this model and engage in a more formal assessment. This may not be possible due to other constraints, but in that case the risks should be acknowledged. Performing mental simulations of possible actions can lead to incomplete scenarios and not fully expose unintended consequences. One important question also remains: What constitutes expertise? This is particularly relevant in light of the Dunning-Kruger effect. Furthermore, we have to recognise that not all decision makers are experts. Klein and Jarosz (2009) studied the problem and tried to reconcile opposing views: One that humans are inherently fallible, suffering from heuristics and biases, and that decisions should follow formal processes, be supported by "hard" evidence and sometimes even left to automated processes. The other placing more confidence in the human nature and saying that it is possible for experts to gain insights and be guided by intuition that is not easy to formally describe, in ways that are more in accordance with reality. These should not, however, be confused with System 1 intuitions. Both arguments have merits. Undoubtedly people suffer from cognitive shortcomings that lead to bad results. At the same time, expertise can offer additional insights that are difficult to explain, but can lead to good outcomes.

There are conditions that dictate in which situations *expertise* can be developed and applied:

- Regular environment - "high validity"[11]
- Opportunity to learn the regularities and practice
- Rapid and unequivocal feedback

[11] While in irregular environments it is impossible to forecast the result of a decision, in low validity environments with weak regularities, it was noticed that algorithms can outperform humans.

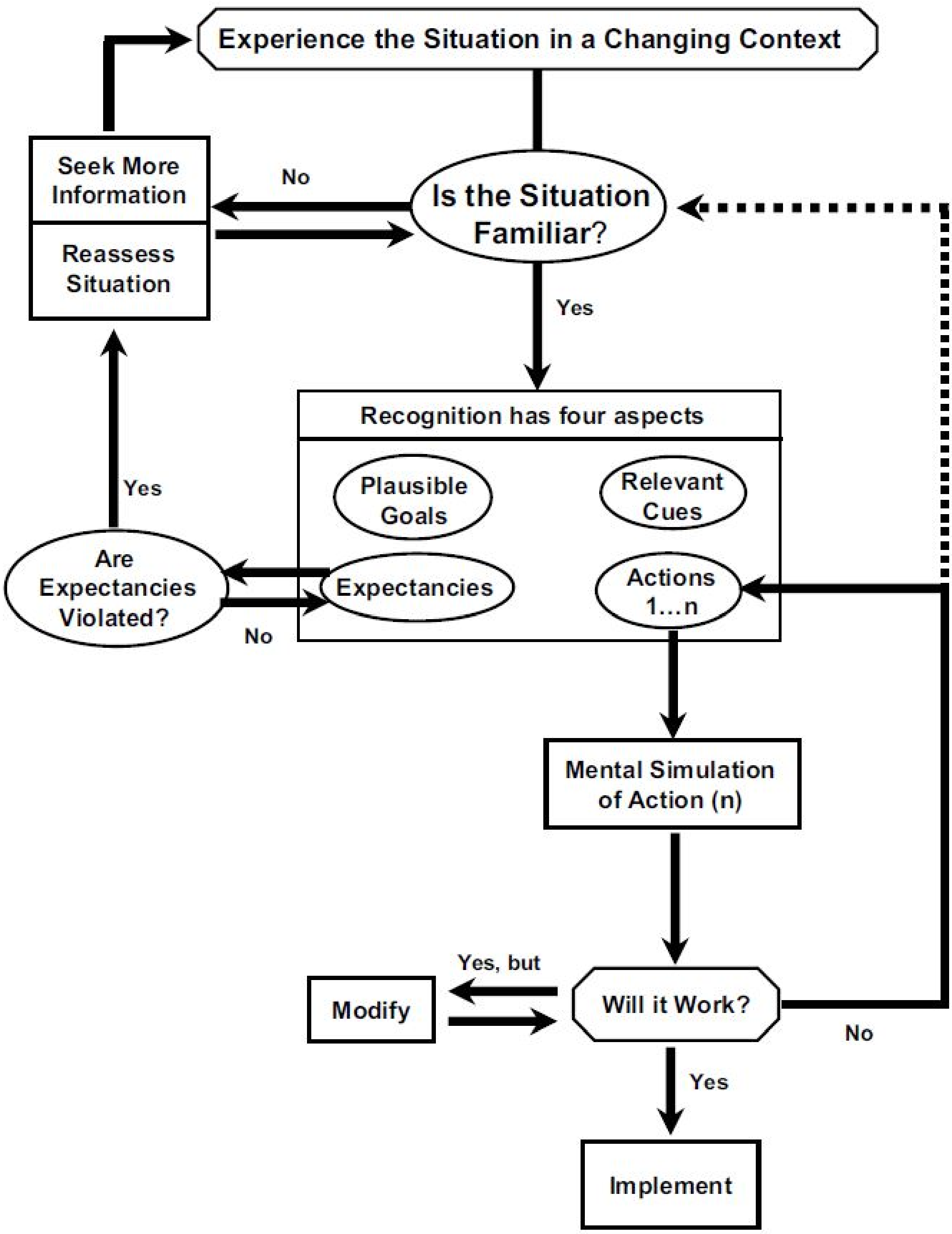

Figure 17: Work flow of the recognition-primed decision model (Klein et al., 1993). When confronted with a decision situation, people will try to identify it as a possibly know scenario (at which experts are better). If nothing out of the ordinary, based on our expectations, makes us break away from the model, we do not analyse all possible solutions to then decide which is the best course of action. Instead, experience leads us to mentally follow through the outcome of a possible solution that seems appropriate and, if it works, we execute it. If we identify problems, we change the proposed solution until finding one that works. It may not be the best, but it is one that will lead to an acceptable outcome (satisfice). This implementation speeds up the decision process and often Naturalistic Decision Making is carried out during emergencies, when time is of the essence.

3.5 A word of caution in a global world

Many of the studies used to develop the frameworks mentioned before were done with people from Western, Educated, Industrialised, Rich, and Democratic (WEIRD) countries, in particular, students. This causes a problem when it comes to draw global conclusions to a very diverse world. Henrich et al. (2010) raise their point with an extreme example:

In the tropical forests of New Guinea, the Etoro believe that for a boy to achieve manhood he must ingest the semen of his elders. This is accomplished through ritualized rites of passage that require young male initiates to fellate a senior member (Herdt 1984/1993; Kelley 1980). In contrast, the nearby Kaluli maintain that male initiation is only properly done by ritually delivering the semen through the initiate's anus, not his mouth. The Etoro revile these Kaluli practices, finding them disgusting.

We must not discard this example as not being relevant because not only similar practices have been found in Aboriginal Australia, Ancient Greece or Tokugawa - Japan, but also many other practices will be sufficiently different in varied parts of the world that they can cause surprise or even shock. The argument is that there is a narrow database of similar people used in behavioural studies and this raises the question of the findings not being universally applicable. For example, when looking at visual perception, Segall et al. (1966) found that American students were the most affected by the Müller-Lyer illusion (shown in § 3.1), while the San foragers of the Kalahari were unaffected by it. They have also noticed differences when it comes to fairness and cooperation in decision making, cognition and analytical versus holistic reasoning, among others, with Western industrialised countries generally occupying one of the extremes. When it comes to the Dunning-Kruger effect, a study by Heine et al. (2001) indicated that Japanese people tended to underestimate their abilities, and saw underachievement as an opportunity to learn. Segall et al. also list a series of differences between educated and uneducated Americans, related to rationalisation of choices, individualism or moral reasoning. Does this mean that everything that has been discussed up to now is of little or no value? No. Not only the diversity of topics covered has involved studies in different contexts, but also Segall et al. refer to many characteristics found to be common among different peoples and their main point, as is of this Section, was to draw attention to the possible dangers of generalisation.

The existence of cultural differences is a commonly discussed topic that should not catch anyone by surprise in this globalised world and so many years past the work from (Hofstede, 1980) and his influential cultural model. Hofstede developed a model based on four (later extended to five) dimensions, *Power Distance*, *Uncertainty Avoidance*, *Individualism*, *Masculinity* and *Long-term Orientation*. Despite its current use in be business world, one should be aware that Hofstede's model has long been criticised for its Eurocentric take on the world (Fougére and Moulettes, 2007), dividing it between a developed and modern side and a traditional and backward side, that reinforces stereotypes and biases.

Another known framework to study cultural differences is that of Trompenaars and Hampden-Turner (1997). This model is based on seven dimensions that deal with interpersonal relationships, time and environment: *Universalism vs. Particularism*, *Individualism vs. Communitarianism*, *Neutral vs. Emotional*, *Specific vs. Diffuse*, *Achievement vs. Ascription*, *Sequential vs. Synchronic* and *Internal vs. External control*.

Lewis (2006), on the other hand, categorises cultures into three groups, with shared commonalities and easier to adapt to: *linear-active*, *multi-active* and *reactive*. Their attributes range from personality traits, to communication, emotional behaviour or how they deal with facts. In addition, Lewis also looks at communication patterns during meetings, which is of relevance when studying the decision-making process. Even neighbouring countries, with assumed similar cultures, can display great differences, as can be seen in Figure 18, related to Finland and Sweden.

Schein (1985) says that "culture is the way in which a group of people solves problems and reconciles dilemmas". We know there are processes that may not work in different places, but at the same time there is a certain uniformity on how humans process information, which is important for the purpose of decision making.

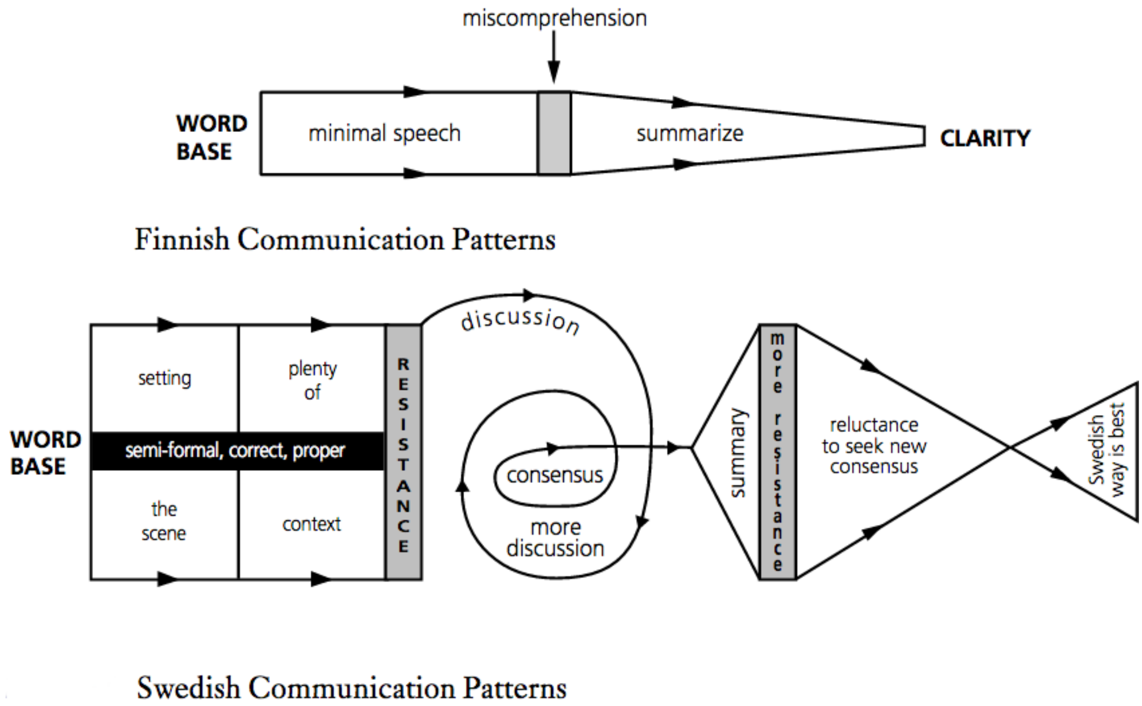

Figure 18: This Figure, adapted from (Lewis, 2006), shows the Finnish and Swedish communication patterns. Despite the proximity of the countries and their shared history, we can see that communication during meetings or negotiations progresses in markedly different ways.

4 Machine

The use of machines to automate or guide processes is not new, but its uses and capabilities have been expanding tremendously to the extent that we are now talking about completely autonomous decision making. It is the purpose of this Chapter to give an overview of Business Intelligence and the technological advances that are making their way into different areas of the business environment, leading to changes in how things are done and even opening up new business models. We must not get carried away, though, by the more publicised extreme cases of digital innovation because these are not the reality for most companies. They do show, however, a possible future. It is important to understand the existing potential, be prepared and adapt it to our concrete cases.

4.1 Business intelligence

We have, until now, been addressing the characteristics of the human decision process, with its many limitations. To face these limitations, we have engaged the aid of *decision support systems*, computerised information systems used to support decision making. These can handle vast amounts of data in a much faster way than humans can, help visualise it and analyse it. *Business intelligence* (BI), which was already introduced in the beginning of this work § 1.1, with its aim of supporting better business decision making, can be called a decision support system.

BI includes the infrastructure, tools, applications, and guidelines that enable access to and analysis of information. It can be applied to many business purposes, such as measurement (performance metrics, benchmarking...), reporting, analytics (data mining, statistical analysis, modelling...), collaboration (data sharing, workspaces...) and knowledge management. Initially, information analysis was centred in the past, taking on a more descriptive role of what had happened (Figure 19). These reports require a considerable amount of manual labour in order to reach a decision and, depending on the data, it may not even be possible to achieve good insights. Better is to have a system in place that allows to understand why things happened, giving us more control and predictability. We are now moving in the direction of having not only forecasts of what will happen, but also a decision of what should be done. This automation may seem increasingly necessary in a world in which customers want real-time responses, but how will these systems be kept in control? Automated high-frequency trading has, for example, cost USD 440m in less than one hour, in 2012, to a company called Knight Capital, or caused a short crash in the Dow Jones in 2010 (Hartford, 2012). Furthermore, as Davenport (2015) inquires, how will humans accept being controlled and told what to do by automatic systems?

There are certainly challenges to be addressed, but there is also plenty to do before most companies face themselves with similar cases. The BI and analytics-related businesses are growing and are in themselves interesting opportunities. Cisco (2016) predicts that global data centre traffic will grow 3-fold from 2015 to 2020, with 92% of it being related to cloud services. Date centre capacity will expand 5-fold and cloud workloads will be dominated (74%) by Software as a Service (SaaS).

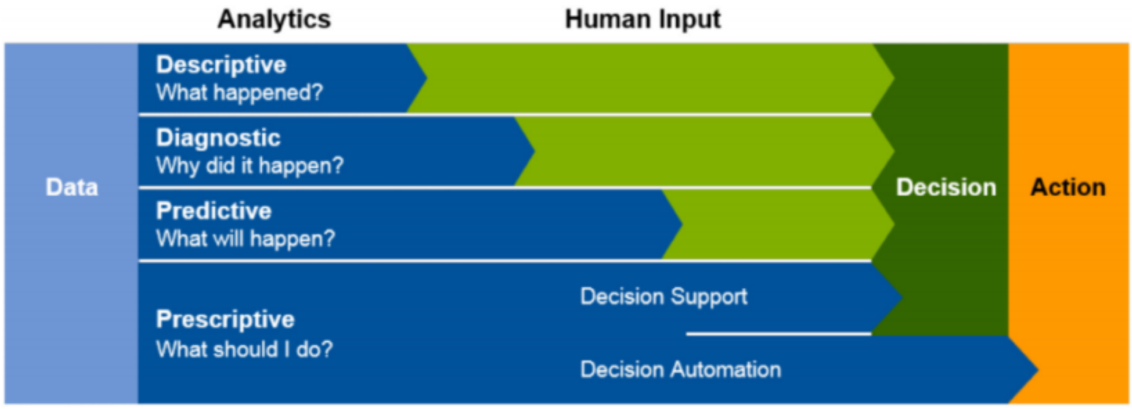

Figure 19: The path from data to actions, from the simplest, backward-looking actions, more linked to reporting, to the more valuable, forward-looking prescriptive analytics that advise on the better course of action and can even be automated (Kart, 2015).

More interestingly, though, are the possibilities arising from companies using a more evidence-based approach and analytics in their operations. Data analytics can be used to derive insights about products, customers, competitors, environment, and the companies themselves. We can see it as coming hand in hand with the whole digitalisation movement. Even simple things as accessing information within a company can pose serious difficulties. With different departments working independently, using different software and storing data in separate information silos, often the sharing of information is not only a technical, but a mentality problem as well (Gleeson, 2013). Figure 20 shows the information gap CEOs face when making decisions. And the problem can be widespread throughout the company. Ries (2011) argues the case of information and metrics to be actionable, accessible and auditable.

While executives say they want to increase speed and sophistication of their decisions (PwC, 2016), two thirds say their decisions are only somewhat or rarely data driven. Furthermore, data can be used as a communication tool, helping to visualise and make sense of the world. The top obstacles to the successful implementation of business analytics, as identified by executives, are departmental silos, resource constraints, complex and diverse business demands, too many "priorities", and lack of data-driven collaborations (Business Week Research Services, 2009). And with any opportunities that arise, so do challenges. Ernst and Young (2014) identify risks connected to Big Data usage in the fields of Governance, Management, Architecture, Usage, Quality, Security, and Privacy. The needs have been identified, the desire is present, there are frameworks to minimise

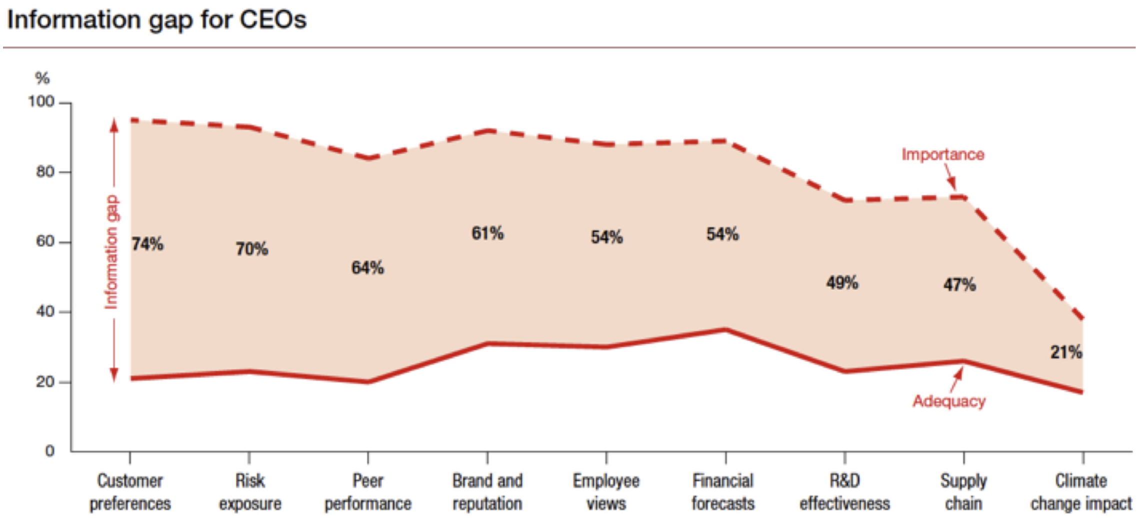

Figure 20: In this image, we can see the discrepancy between the importance of the information CEOs use to make business decisions (dashed line) and, as solid line, the adequacy of the information they have at their disposal (PwC, 2010).

risks, businesses just need to take a step forward and embrace the future.

According to IBM (2015), the use of advanced analytics is being pushed forward by four trends:

- Internet of Things - 50 billion connected things, by 2020
- Consumer empowerment - more informed, high expectations
- Big Data - large volumes, variety, at high speed and with a certain uncertainty
- New business models - relying on the power of the internet to provide services

These are accelerated by:

- Increasing costs pressure
- Advancing technical capabilities
- A new breed of younger and technologically proficient CXOs
- Constant success stories

4.2 Decision analysis

Decision analysis attempts to assist decision makers by addressing decisions in a formal manner. Through it, we hope to reduce subjectivity and guide people to think systematically about the objectives, structure and uncertainties of the problem, modelling them in a quantitative way. It is having an increasing impact in the way organisations make strategic and tactical decisions, enabled by advances in modelling tools and computational power. Due to its formalism, it is of a prescriptive nature that contrasts with the descriptive view of decision making, meaning the way people actually make decisions. We already know that there are situations in which people resort to intuitive decisions, but have also seen that these scenarios must meet certain conditions. In general, models can yield better predictions than humans (Dawes and Corrigan, 1974), helping with noise reduction, not just from the human judgment part, but even from noisy data (Fischer and Paleologou, 1992). In addition, this is just a set of tools that people may misuse or decide to ignore, in particular when confronted with risk. Uncertainty is a fact of life and most models will be of a probabilistic nature. They cannot control the subjective human reaction to risk. But it is possible to mitigate it by establishing *a priori* decision rules. Furthermore, in many repetitive decision scenarios, it can be automated and bypass the need for human input.

There are various tools used in the context of decision analysis. While explaining how to use them in detail is beyond the scope of this work, a few common methods will be described.

Visualisation is important for structuring and understanding the problem. The most common tools are *decision trees* and *influence / decision diagrams*. Decision trees are flowcharts with nodes symbolising sequences of decisions or events that expand into branches with the outcomes. Influence diagrams are acyclic directed graphs with events as nodes (decision problems, chances or consequences), connected by arcs of information or dependencies.

Tackling each decision and its possible consequences and uncertainties usually involves modelling the problem in a mathematical way. When there is one single objective, it will be a question of maximising it, but often there are multiple objectives that will require tradeoffs.

There are a wealth of tools available to model, evaluate and visualise these decision possibilities, from spreadsheets to programming languages, such as R[12] and analytics programmes with different level of features packaged in a way that is more accessible to those without the specific mathematical and computational training to develop tools from scratch. A common trend nowadays is to have these available as a *Software as a Service*.

4.2.1 Automation

Many decision situations are repetitive and, if they can be handled by decision analysis tools, a logical step is to automate them, reducing the need for human labour. This is particularly valuable in high volume - low variability tasks situated in the *known* quadrant of the Cynefin framework. In this case, a process and rules can be used to input data, analyse it and produce an outcome, something which done, for example, in credit card applications.

Automation was a first step in shifting the control over to machines and is perhaps better illustrated by robotisation, where the implementation is more visible. But with the internet and the growth of Big Data, automating processes became a necessity in order to process large quantities of data in the short times required by the digital age. And that has had a profound impact on how traditional areas, such as advertising, work. Whereas in the past, advert space was bought in advance to be placed in physical support, now websites open a bidding process that handles proposals for certain advert space, based on rules by the website and the advertisers, autonomously deciding what to show and to whom, in the time it takes for a page to load.

More complex tasks in high variability environments or without discernible patterns where rules can be easily implemented had been outside automation capabilities until computational advances allowed for the implementation of *artificial intelligence*. This is the stage at which we are now, with different industries at different levels of the innovation adoption curve (Rogers, 2003) and it is, therefore, important to understand what artificial intelligence means for businesses and for the decision-making process.

[12] `https://www.r-project.org/about.html`

4.3 Artificial Intelligence for business people

A computer would deserve to be called intelligent if it could deceive a human into believing that it was human. - Alan Turing

With the growing ability of machines to learn complex tasks and make decisions that were until now reserved for humans, it is important to understand what this artificial intelligence (AI) is, what new possibilities it brings to businesses and how it will interact with people. Often, discussions concerning AI applications to businesses revolve around case examples that do not go much in depth and showcase advanced applications that are not applicable to most companies. On the other hand, more detailed information from technical sources quickly becomes too complex.

What is important is to prepare people to recognise the needs and potentials of AI, identifying opportunities and preparing the company to employ AI projects. While, specific technical skills are needed to implement these projects, it is necessary for executives and managers to have an understanding of what AI is, what it can and cannot do, and what are the requirements. It is not useful to want to employ artificial intelligence without being prepared for it and having identified business cases that can be served by it.

4.3.1 What it is

Learning is any process by which a system improves performance from experience. - Herbert Simon

The processes described in the Decision Analysis Section rely on our ability to model the problems. But some situations may involve relationships and interdependencies that are too complicated for that to be possible. In these situations, we may apply an artificial intelligence, a machine that has the ability to function in similar ways to a person, but with extraordinarily higher capacity. This intelligence, similarly to the human case, can often have a learning phase, what is called *Machine Learning* (Samuel, 1959).

In traditional programming, we provide data, as inputs, and a program, as the set of rules, to a computer that then gives us the results, as outputs. In machine learning, a computer with a machine learning algorithm is given the data and results (inputs and known outputs) in order to figure out the rules without being explicitly programmed - the learning process. These may be too complex for a human to derive directly from the real world or understand, but can be generated by the algorithm and then applied in the traditional programming model (Fig. 21).

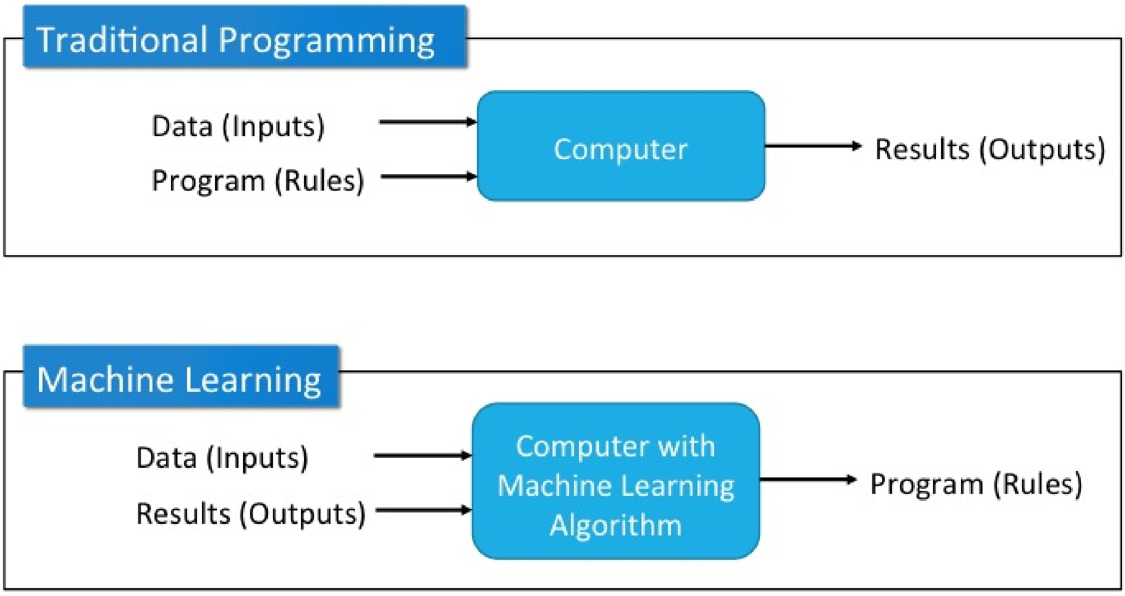

Figure 21: Differences between traditional programming and machine learning. While in traditional programming data and a set of rules are given to a computer in order to generate results, to teach a machine learning code both data and already known results are given so that the computer can figure out the rules.

While many of mathematical bases and techniques were already being developed in the 18^{th} century, and machine learning seeds appeared by McCulloch and Pitts (1943) who proposed a model for a formal neurone and Turing (1950) who described a “learning machine”, proper implementation was not possible until more recently due to computational limitations.

4.3.2 What it can do

The artificial intelligence use cases that are most shared paint an often unrealistic picture of AI’s capabilities and applications. In most cases, data is used to generate a simple

Table 3: Problems machine learning can be used to solve, followed by the generic type of algorithm and application examples.

Problem	Type	Examples
Predict values	Regression	Market forecasting
		Growth prediction
		Advertising popularity prediction
Discover structure	Clustering	Recommender system
		Targeted marketing
		Customer segmentation
	Anomaly detection	Fraud
		Cyber attack
Predicting categories	Classification	Image classification
		Diagnostics
		Customer retention

response and the type of algorithm depends on the nature of the data, the question we are trying to answer and the available time.

We often see information regarding machine learning structured in a way that starts with the different types of algorithms, but that is less clear for someone trying to solve a specific problem. We will instead group them first into problem categories, followed by type of algorithms and examples of applications (Table 3).

The actual learning process can work in different ways. You may hear talking about supervised, unsupervised, semi-supervised and reinforcement learning. Supervised learning algorithms (the case shown in Fig. 21) learn to make predictions based on a set of examples, the input and labeled output data (tagged with the correct answer), which they can later apply to new data. In unsupervised learning, there are no labeled data, meaning there is no “teacher” and the programme must learn on its own. Semi-supervised lies in the middle and often happens because the cost of labelling data can be high as it requires human intervention, so there are mixed labeled and unlabelled data. Reinforced learning uses trial and error and feedback from the environment to learn the best course of action.

Usage of these methods is enabling automatic detections of features in pictures (object or face recognition), assessing probabilities of loans being repaid, probabilities of a person clicking a specific ad, recognising and translating languages, assessing the likelihood of a certain part to fail and used in preventative maintenance, detecting and tracking position of obstacles in self-driving cars, *etc*. In general, artificial intelligence is <u>better</u> at:

- repetitive tasks
- solving problems that involve crunching large, well-organised data sets
- speed
- making fewer errors when evaluating patterns on big data

and worse:

- dealing with ambiguity
- understanding nuances
- with unreliable data.

Artificial intelligence's capabilities have been expanding continuously and often tested against humans. Some notorious results were Deep Blue's victory agains Garry Kasparov at chess in 1997, Google Deep Mind's victory against Lee Sedol at Go in 2016 or that IBM's Watson could diagnose cancer better than doctors. These machines are the state of the art and are used for the most demanding cases, far from the reality of regular businesses, but Brynjolfsson (2012) reported that companies engaging in data-driven decision making performed at rates four to six percent higher than their peers in a number of different categories, including productivity and profitability. This does not mean replacing human deciders by machines, but using the capabilities of advanced technology to support decisions, compensating for the human shortcomings that were discussed earlier. Despite the advantages they demonstrate, according to PwC (2016) the majority of strategic decisions are based on human judgment. The next step for executives is to incorporate AI into their strategies. This means understanding where value is created and what is hard to copy - how to derive sustainable competitive advantage. Then start small and simple, while keeping employees informed. If they understand the value of AI for the organisation, they will be less likely to oppose it and will, in fact, bring more value to it.

4.3.3 Drawbacks

We have seen that there are problems machines still cannot tackle. But even those where artificial intelligence can be applied, there still may be limitations or unintended consequences.

AI is data hungry! In particular, it needs good quality data, something that is often lacking in real life. Machine learning projects can use large amounts of human labour to sort, organise, cleanse and prepare data to be analysed. Businesses should think strategically and identify future uses of AI, preparing for it in advance.

AI can be fooled! Data are a very important part of decision making, both for people and machines. In this digital era, it is increasingly easy to spread false information. At the same time, it is difficult for machines to recognise it. We witnessed the unfortunate results of fake news taking over social media after Facebook decided to swap its editorial team for algorithms. This led to several fake stories emerging as trending (Thielman, 2016) and ensued a backlash against Facebook. At the end of 2016, the company decided to collaborate with fact-checking entities, such as Snopes, to address this false information issue (Snopes, 2016), which has yet to be resolved.

Even though AI has managed to beat humans in image recognition in 2015 (Johnson, 2015), it has now been shown it can also be fooled by changing a single pixel of an image (Su et al., 2017) or made to achieve high confidence predictions of unrecognisable images (Nguyen et al., 2014).

AI can be biased! This can lead, for example, to automation of discrimination. Biases can be picked up by machine learning because training sets are drawn from a biased reality. Buolamwini and Gebru (2018) noticed that facial analysis software presented better accuracy with white males. Zhao et al. (2017) report that image recognition algorithms have a gender bias, associating certain tasks, like cooking, more with women to the point that they misclassify a man in a kitchen as a woman. Algorithms not only mirrored the biases, but amplified them. Not only the data, but also the training can lead algorithms astray, due to improper reward feedback. This is a problem that also happens with people. We have known for a long time that performance rewards decrease people's performance in tasks that involve problem solving, creativity or concentration (Ariely et al., 2009) and that they reduce motivation Deci et al. (1999). Yet, this kind of incentives is still widely used in the business setting. Likewise, rewarding algorithms in the wrong way during the learning phase will lead them to wrongly understand the objectives of the task. This has happened with YouTube, which aims at keeping people watching videos. The AI noticed that people watch outrageous videos more, so it started favouring showing conspiracy-related videos, not only what should be related to the person's history and interests (Swearingen, 2018).

AI can be taken advantage of! In 2016, Microsoft released an AI chatbot, Tay, in Twitter. It was programmed to learn human behaviour through interactions with other users. After 16 hours, it had to be shut down because the tweets had become sexist, vulgar and racist (Vincent, 2016). While this behaviour could have been partly learned from a biased world, it was to a greater extent caused on purpose by other users.

5 Human and Machine working together

Resistance is futile. - The Borg

The discussion revolving around the increased use of artificial intelligence often takes on a *human vs. machine* approach. This leads to a dichotomal view of the current situation that results in fears and resistance to change. We have shown that there are strengths and weaknesses in both sides. While we should certainly choose the best tool for the job, this will probably mean working together. It will be very difficult to remove the human component from decision making, but it should be evidence-based and taking advantage of the technological possibilities. Artificial intelligence is one more tool for business intelligence, with plenty of potential and where automated processes have room to expand. This instils the fear of people being replaced by machines and loss of jobs. It is true that it will happen for particular tasks, but it will also free people to do other types of jobs. We need to understand how people interact with this technology and prepare them to make use of the possibilities offered by it. When it comes to implementing technology, companies are still too focused on technical skills, employing people who may fail to see the big picture and understand the business context. At the same time, they lack people with the needed technological knowledge in places where they can really influence the business, placing data scientists far from the decision-making processes (Redman, 2018). A large number of executives still relies mostly on intuition to drive decisions (Figure 22) and we now know the dangers it entails. Overall, more workers should be aware of the needs and potential of AI, so they can think strategically and help reduce the high failure rate of analytics projects (Demirkan and Bulent, 2014).

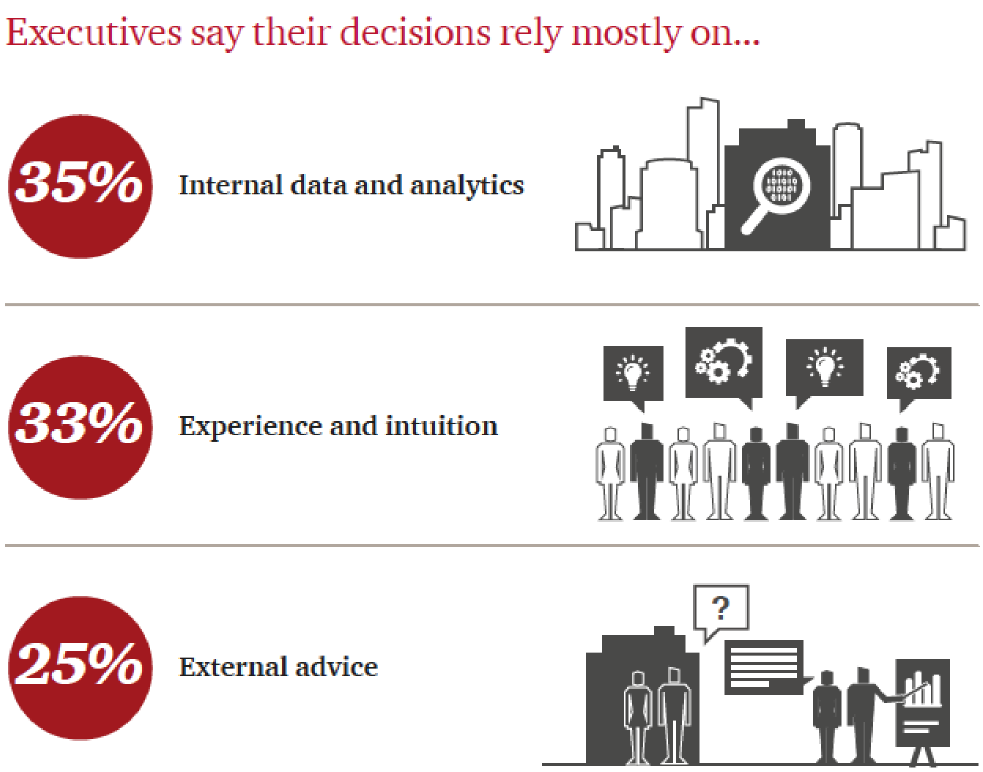

Figure 22: Many decisions are still not being based on data or analytics, leaving them vulnerable to the shortcomings of human nature (PwC, 2016).

Daugherty and Wilson (2018) explores this “missing middle” of human and machine hybrid activities, where collaboration leads humans to complement machines and machines to increase the human power. This close interaction will also pose new challenges, if it becomes too complex, it will not be effective. Some companies are already successfully experimenting with such hybrid activities. For example, Stitch Fix[13] wants to replace its customers when it comes to shopping for clothes. They rely on the customers buying what they send them and for that they use advanced analytics that goes beyond finding similar items from the customers’ past. They are able to detect new trends early, keep detailed measurements of the garments and understand what fits each of their two million customers, be aware of personal tastes and deliver something slightly different, a good surprise. The use of human stylists allows the company to check the automated recommendations, understand and comply with direct requests, and adapt to specific needs (such as a particular event or considerable weight change) in ways the algorithms cannot. They are even starting to use data science and stylists to design clothes. By having the data science team reporting to the CEO, they avoid one of the errors identified earlier by Redman (2018), and treat data science not as a technical area of the company, but

[13] https://www.stitchfix.com/

a very strategic one, connected to decision making. As their CEO says, “A good person plus a good algorithm is far superior to the best person or the best algorithm alone” (Lake, 2018).

While the prospect of leaving more basic, repetitive, time-consuming tasks to machines is appealing, it also makes us think how humans will learn if the typical entry-level tasks are given to machines. This leads to the subsequent problem of supervision that becomes more extreme in complex tasks that can directly affect the lives of people, such as investing their savings (Ponczek, 2018). And the use of algorithms is becoming so ubiquitous that we may be influenced by them without realising. YouTube, Google’s search and Facebook’s news feed algorithms serve as filters of information for billions of people. Algorithms are used to give us a credit score, to decide who gets a job interview, or evaluate college applications. Several states in the USA are using computer models to decide lengths of prison time or set bail amounts (Schuppe, 2017), which some critics have accused of perpetuating racial bias (Dressel and Farid, 2018).

If humans are completely removed from the decision-making process, which safeguards would there be in case of malfunction? In 1983, Soviet early warning satellites detected and inbound intercontinental ballistic missile. That proved later to be a false signal caused by the alignment of the Sun, clouds and the detection satellites. An automatic response system would have led to a nuclear war. In this instance, however, lieutenant colonel Stanislav Petrov, on duty at the Soviet Air Defence Forces and whose responsibility was to launch the counter-attack, noticed details that did not make sense. His expert intuition led him to attribute the signal to a malfunction of the system and not to a real attack. He was right (Bennetts, 2017).

Finally, there is the question of acceptance. Who is the boss? How well will people accept being directed by a computer programme and what will happen in case of disagreement? How likely will people be to overrule AI’s findings or manipulate information to fit a personal idea?

Human and machines complement each other. At the moment, people still dominate the decision-making process and machines are increasingly being used on tasks for which they are better suited. But the future lies in cooperation that will enhance capabilities of what people or machines can give us separately.

6 How to improve decision making

We set off on a journey to discover how decisions are made and examined what affects the quality of decisions. In particular we explored human cognitive shortcomings and how data-driven decisions can be the basis for a more grounded approach. The digitalised world has given us decision support systems that have evolved into artificial intelligence. This also has its limitations and picks up many of the problems that affect people, but can also bring huge possibilities to use data in a way humans are not capable of. Having looked at the decision-making context and the decision makers, being them humans or machines, what steps should be employed to increase the quality of decision making? There is no simple solution, but there are ways to minimise errors or their impacts.

We first need situational awareness to understand the complex context of decision making, which is acted upon by pressures and constraints. It is also important to know the strengths and weaknesses of humans and machines in order to choose the best tool for the specific situation and to mitigate the risks that can be cause by the shortcomings of each decision method.

Humans are an important part of the decision process. Only them can understand the goals and the complexity of the real world. Even in the cases where programmes will be responsible for the data-crunching work, AI projects will be driven by humans, implemented by humans and need to be accepted by them. It is therefore important to guard against the human cognitive shortcomings, while having in mind that they will not disappear.

– Do not rely on “common sense” and begin inquiries with an open mind, even to the possibility of answers we do not want to hear. We should be critical when evaluating information and possible outcomes, and require evidence-based arguments.

– Do not multitask. This increases susceptibility to fall into cognitive traps and make errors. Prioritise tasks and concentrate on a problem at a time or on similar processes (such as replying to emails), take a break and give time to your pre-frontal cortex to process ideas. This may not always be easy, not only due to time pressures, but also the work environment where people may be perceived as lazy. The growing trends of open floor offices only adds to this pressure of "looking busy", in addition to being a source of distractions.

– It is better to respond than to react. Reactions are instant. They can be driven by beliefs, biases and emotions. A response is thought out, purposeful, taking into account the available information and with long term implications in mind. It is often more fluid if prepared in advance. This may be a problem because people tend to be positive about their forecasts, they want to succeed and dislike imagining bad outcomes or facing problems. Due to internal workplace politics, they may even hide them. But, as Benjamin Franklin said, "By failing to prepare, you are preparing to fail".

– In order to reduce susceptibility to heuristics and biases, we should[14]:

- Conduct training
  - to raise awareness and knowledge about heuristics and biases.
  - on statistics.
- Have a healthy dose of skepticism - force System 2 to engage.
- Require reasoning and evidence-based arguments.
- Focus on goals.
- Look for information that disproves your believes - attempt to falsify, not confirm your opinion or findings - and consider competing hypotheses.
- Take the outside view (Kahneman, 2011, p. 340) - Start with similar cases before considering the specifics of your individual case.
- Do a *premortem* (Klein, 2007) - When a decision path is chosen, imagine some time has passed and the outcome had been a disaster and try to explain why.
- Resist the temptation to create meaning out of random events.
- Validate information and use different sources, including inputs from different people.
- Think probabilistically - Look for base-rate statistics and reference-class forecasting.

– When attempting to reduce noise:

[14] Some advice was already given in §3.3.2 for the mentioned biases.

- Use algorithms when they are better suited for the task.
- Structure the judgment task - directs people to the same facts in the same way. Rules and guidelines limit subjective judgment.
- Use multiple independent raters.

– Remember that for expert judgment to be of value, one needs three conditions:

- Regular environment.
- Opportunity to learn the regularities and practice.
- Rapid and unequivocal feedback.

– Implement quality assurance for decisions.

Many of the advice listed here have been tested or come from observations. For example, Tetlock et al. (2014) analysed the results from a large forecasting tournament in the field of geopolitics and identified the characteristics of the winner project: (a) cognitive-debiasing training, (b) incentivising rigorous thinking, (c) skimming top talent into elite collaborative teams, and (d) fine-tuning algorithms for retrieving greater wisdom from crowds. Similarly, also a company could apply these principles to improve performance and the example shows the collaboration between human judgment and machine. On a later publication, Mellers et al. (2015) looked at the traits of individuals that excelled in forecasting: (a) higher cognitive ability, political knowledge and open-mindedness, (b) training in probabilistic reasoning and participation in collaborative teams, (c) practised the skill of forecasting and updated their beliefs frequently based on current events.

Machines are increasingly present in our lives and in the decision-making context, either analysing data and providing guidance, or as autonomous deciders. In many situations, they are superior to humans, but not only they do not eliminate some of the human flaws, they bring new ones and do it at a larger scale.

– Understand the potential of business intelligence systems and AI and the situations where they should or can be implemented.

– See AI as a strategic choice that needs a reason to exist. It is meant to solve a problem. We see, with the sharing of interesting success cases, companies wanting to implement

AI, but without a goal and without being prepared for it.

– To reduce errors we should:

- Have in mind that AI also fails.
- Employ algorithms to address adequate problems.
- Pay close attention to data quality.
- It is a discovery process that can use the LEAN startup cycle (Ries, 2011): *build, measure, learn.*
- Test different algorithms for your specific case.
- Implement oversight.
- Think of how algorithms can work with people.
- Do not forget interaction with the human component. Think of interface, acceptance and compliance.

Decision errors will not disappear, but there is a wealth of information from different fields that can help individuals and organisations minimise them. And we should not forget that this is the first step. A successful strategy will also require a successful implementation.

7 A peek into the future

There is no magic crystal ball. Over 50 years ago, the 1964 World Fair in New York City was themed as “The World of Tomorrow”. Their view of what our society should be today included hotels on the ocean floor, colonies on the Moon and flying cars. We now see their predictions were far off. The future is hard to predict and it is a challenge to prepare for things that do not yet exist. But we can detect trends and how technology is taking an increasingly more important role in our lives, being that social or at work. Often the discussion hovers towards the replacement of human labour by automation. Nedelkoska and Quintini (2018) estimates the risk of automation for individual jobs in 32 OECD[15] countries (Figure 23. They found that about 14% of jobs in the studied countries are highly automatable, with further 32% suffering significant changes. There is a high variability among countries, better explained by organisational differences than by differences in economic sectors, but which will affect mostly jobs in manufacture, agriculture and some

[15] Organisation for Economic Co-operation and Development

services, with higher impact in low-skilled jobs. It was also found that automation is more likely to affect youth employment. Education and requalification will be important.

Several economists have repeatedly attempted to predict the impact of new technologies on labour, estimating to which extent they would directly replace humans, but these predictions have so far proved erroneous or premature: (Acemoglu and Restrepo, 2016). Furthermore, there are often unexpected consequences, such as substituting bank clerks by automated teller machines leading to job creation due to lowering the cost of maintaining a bank agency (Bessen, 2015, Fig. 7.1). And automation can lead to the creation of new tasks, which directly benefits high-skill labour. This is, when it works. For some tasks humans still have an advantage, even in traditionally automated industries such as car manufacturing. Tesla[16] had to bring back humans to the production line after robots had slowed down the Model 3 production (Gibbs, 2018).

We must also not forget the potential of data-related industry in itself and how it can affect other industries. Purdy and Daugherty (2017) consider artificial intelligence a new factor of production that can help increase a stagnated profitability.

These considerations are more about how people will work in the future and it is natural to be concerned about jobs. But what about decision making? Humans will be humans. It is difficult to change human nature, but there is a growing awareness of how we process information and perform decisions that is being incorporated in the business world. What may also be possible is to improve some physical limitations, such as memory, with implants already being tested (Powell, 2018). Machines may be replacing humans, but enhanced humans will have the ability to perform tasks until now reserved to machines. Decisions made by machines can reduce the chances of some typical human errors occurring, but they are not yet able to eliminate them. And in some cases, they change the type or errors being done, with the potential to have a larger reach. Nonetheless, we are witnessing a rapid evolution of these systems and can expect them to become

[16] `https://www.tesla.com/`

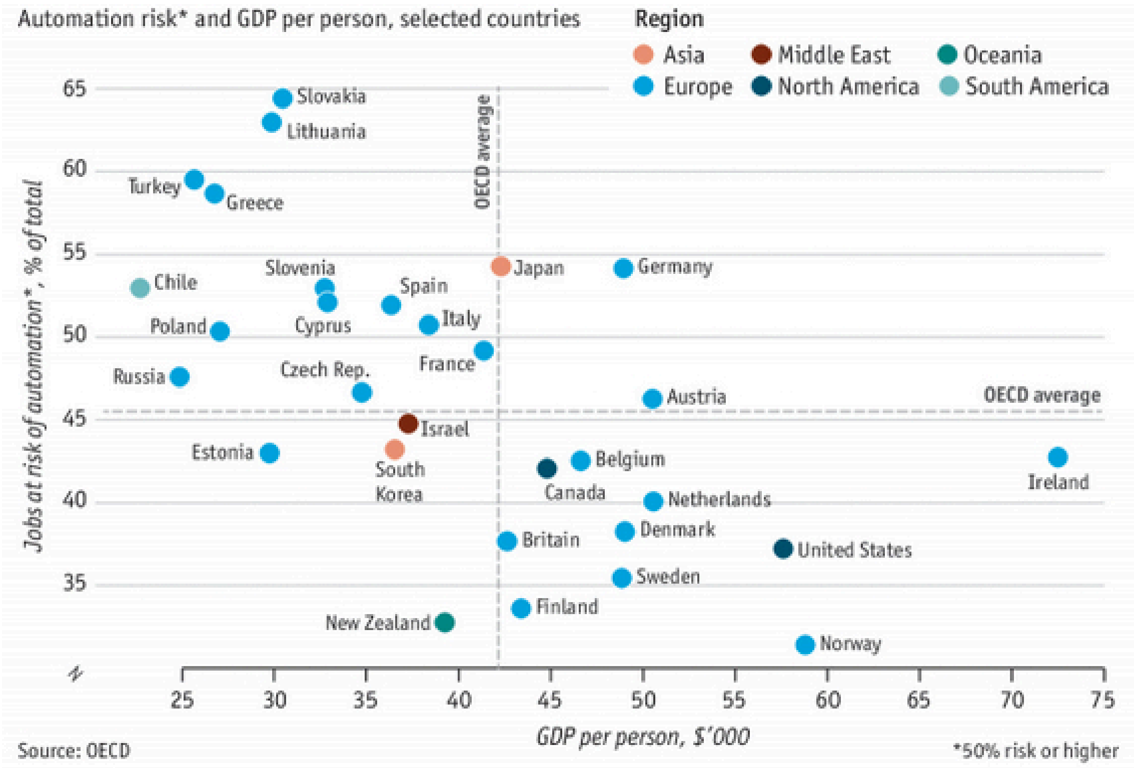

Figure 23: This Figure from The Economist (2018), based on data from Nedelkoska and Quintini (2018), plots a sample of studied countries based on Gross Domestic Product *per capita*, in the x-axis and the percentage of jobs at risk of automation, in the y-axis.

increasingly more autonomous decision makers and action takers.

8 Conclusion

Is it as Loukides (2011) argues, that "The future belongs to the companies and people that turn data into products"? There are certainly many examples of a growing interest in taking advantage of data for more evidence-based decisions. And the concept in itself is not a new one, despite the slow transition from the medical and scientific fields to the business environment. Moreover, people in general are taking advantage of these technological advances, using them to change consumer behaviour (the empowered consumer) or drive social changes. Data usage is not something bound to the business environment, it connects even with democracy (Therriault, 2016) and is shaping elections.

This work attempted to look at decision making in an increasingly digitalised era in a twofold way. By 1) collecting a wealth of relevant information that not always reaches the business world and 2) combining two fields that are usually discussed separately, the human behaviour and the technological advances.

The human component in decision is important and not disappearing, but human failures need to be acknowledged. There is not a case for favouring humans, like the supporters of Naturalistic Decision Making argue, nor machine deciders, despite the lengthy exploration of human flaws. We should embrace them both.

Organisations cannot ignore the benefits of data-driven decision making and all the new insights made possible by technological advancements. With such transformations also come risks, not only of badly implemented strategies, but even of acceptance or of moral dilemmas, such as the ones faced by self-driving vehicles (Greenmeier, 2016) and organisations must be aware of them in order to succeed. Further work is needed to track and assess the outcomes of automated decisions and the possible conflicts between humans and machines. In case of disagreement, who has the final word?

It is hard to predict what the future entails, it is not only work, but society, that is in constant change.

References

Acemoglu, D. and Restrepo, P., 2016. *The race between machine and man: Implications of technology for growth, factor shares and employment*, National Bureau of Economic Research working paper 22252. [Online] Available at <http://www.nber.org/papers/w22252> [Accessed 27.04.2018].

Acree, T., 2013. '*Painting Flavor, The modulation of odor perception by vision*', Presented at the American Chemical Society - Annual Meeting, New Orleans.

Adair, A., Hutchison, N., MacGregor, B., McGreal, S. and Nanthakumaran, N., 1996. *An analysis of valuation variation in the UK commercial property market: Hager and Lord revisited*, Journal of Property Valuation and Investment 14(5), 34–47.

Aileron, 2017. *10 Reasons Why Strategic Plans Fail*, Forbes . [Online] Available at <https://www.forbes.com/sites/aileron/2011/11/30/10-reasons-why-strategic-plans-fail/#6382562f86a8> [Accessed 25.04.2018].

Albright, J., 2017. *Normalization of Deviance*, Business & Commercial Aviation pp. 40–43.

Anderson, J. Q. and Raine, L., 2012. *Millennials will benefit and suffer due to their hyperconnected lives*, Pew Research Center. [Online] <Available at http://www.pewinternet.org/files/old-media/Files/Reports/2012/PIP_Future_of_Internet_2012_Young_brains_PDF.pdf> [Accessed 27.04.2018].

Anthony, A., 2016. *Is free speech in British universities under threat?*, The Guardian . [Online] <Available at https://www.theguardian.com/world/2016/jan/24/safe-spaces-universities-no-platform-free-speech-rhodes> [Accessed 16.12.2017].

Ariely, D., Gneezy, U., Loewenstein, G. and Mazar, N., 2009. *Large Stakes and Big Mistakes*, The Review of Economic Studies 76, 451–469.

Banja, J., 2010. *The normalization of deviance in healthcare delivery*, Business horizons 53(2).

Barends, E. Rousseau, D. M. and Briner, R. B., 2014. *Evidence-Based Management: The Basic Principles*, Center for Evidence-Based Management.

Baron, R. A., 1997. *The Sweet Smell of... Helping: Effects of Pleasant Ambient Fragrance on Prosocial Behavior in Shopping Malls*, Personality and Social Psychology Bulletin 23(5), 498–503.

Bennetts, M., 2017. *Soviet officer who averted cold war nuclear disaster dies aged 77*, The Guardian . [Online] Available at <https://www.theguardian.com/world/2017/sep/18/soviet-officer-who-averted-cold-war-nuclear-disaster-dies-aged-77> [Accessed 20.04.2018].

Benson, B., 2016. *Cognitive bias cheat sheet*, Better Humans . [Online] Available at <https://betterhumans.coach.me/cognitive-bias-cheat-sheet-55a472476b18> [Accessed 23.04.2018].

Bessen, J., 2015. *Learning by Doing: The Real Connection between Innovation, Wages, and Wealth*, Yale University Press.

Botvinick, M. and Cohen, J., 1998. *Rubber hands ‘feel’ touch that eyes see*, Nature 391, 756–.

Brehm, J. W., 1956. *Postdecision changes in the desirability of alternatives*, Journal of Abnormal and Social Psychology 52, 384–9.

Brynjolfsson, E., 2012. *Strength in Numbers: How Data-Driven Decision Making Drives Innovation and Productivity*, *in* ‘The Premier Business Leadership Series: What the Executives Say’, pp. 9–10.

Buolamwini, J. and Gebru, T., 2018. *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, Proceedings of Machine Learning Research 81(1), 1–15.

Business Week Research Services, 2009. *Driven by Data: The Importance of Building a Culture of Fact-Based Decision-Making*, SAS . [Online] Available at <http://www.sas.com/whitepapers/index.html> [Accessed 11.11.2016].

Canadian Task Force on the Periodic Health Examination, 1979. *The Periodic Health Examination*, Can Med Assoc J. 121(9), 1193–1254.

Cisco, 2016. *Cisco Global Cloud Index: Forecast and Methodology 2015 □ 2020*, Cisco Public . [Online] Available at <https://www.cisco.com/c/dam/m/en_us/service-provider/ciscoknowledgenetwork/files/622_11_15-16-Cisco_GCI_CKN_2015-2020_AMER_EMEAR_NOV2016.pdf> [Accessed 27.04.2018].

Clance, P. R. and Imes, S. A., 1978. *The imposter phenomenon in high achieving women: dynamics and therapeutic intervention*, Psychotherapy: Theory, Research & Practice 15(3), 241–247.

Cowen, A. S. and Keltner, D., 2017. *Self-report captures 27 distinct categories of emotion bridged by continuous gradients*, Proceedings of the National Academy of Sciences .

Damásio, A., 1994. *Descartes' Error*, Penguin.

Danziger, S., Levav, J. and Avnaim-Pesso, L., 2011. *Extraneous factors in judicial decisions*, Proceedings of the National Academy of Sciences of the United States of America 108(17), 6889–6892.

Daugherty, P. R. and Wilson, H. J., 2018. *Human + Machine. Reimagining Work in the Age of AI.*, Harvard Business Review Press.

Davenport, T. H., 2015. *The Rise of Automated Analytics*, The Wall Street Journal . [Online] Available at <http://blogs.wsj.com/cio/2015/01/14/the-rise-of-automatedanalytics/> [Accessed 13.11.2017].

Dawes, R. M. and Corrigan, B., 1974. *Linear models in decision making*, Psychological Bulletin 81(2), 95–106.

Deci, E. L., Koestner, R. and Ryan, R. M., 1999. *A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation*, Psychological Bulletin 125(6), 627–68.

Demirkan, H. and Bulent, D., 2014. *The Data Economy: Why do so many analytics projects fail?*, Analytics Magazine . [Online] Available at <http://analytics-magazine.org/the-data-economy-why-do-so-many-analytics-projects-fail> [Accessed 24.04.2018].

Devens, R. M., 1865. *Cyclopædia of Commercial and Business Anecdotes*, Appleton and Company.

Dressel, J. and Farid, H., 2018. *The accuracy, fairness, and limits of predicting recidivism*, Science Advances 4(1).

Einhorn, H. J., 1974. *Expert judgment: Some necessary conditions and an example*, Journal of Applied Psychology 59(5), 562–571.

Eisenhardt, K. M., 1989. *Agency Theory: An Assessment and Review*, The Academy of Management Review 14(1), 57–74.

Endsley, M., 1995. *Toward a Theory of Situational Awareness in Dynamic Systems*, Human Factors 37(1), 32–64.

Ernst and Young, 2014. *Big Data - Changing the ways businesses compete and operate*. [Online] Available at <http://www.ey.com/Publication/vwLUAssets/EY_-_Big_data:_changing_the_way_businesses_operate/%24FILE/EY-Insights-on-GRC-Big-data.pdf> [Accessed 24.11.2017].

Evans, J. S. B. T., 2008. *Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition*, Annual Review of Psychology 59, 255 – 78.

Festinger, L., 1957. *A Theory of Cognitive Dissonance*, Stanford University Press.

Fischer, M. J. and Paleologou, S. A., 1992. *Decision Making in the Presence of Noise*, *in* J. Buchmann, J. Ganzinger and W. J. Paul, eds, 'TEUBNER-TEXTE zur Informatik', Vol. 1, Vieweg+Teubner Verlag, Wiesbaden.

Foerde, K., Knowlton, B. J. and Poldrack, R. A., 2006. *Modulation of competing memory systems by distraction*, Proceedings of the National Academy of Sciences 103(31), 11778–11783.

Fougére, M. and Moulettes, A., 2007. *The Construction of the Modern West and the Backward Rest : Studying the Discourse of Hofstede's Culture's Consequences*, Journal of Multicultural Discourses 2(1), 1–19.

Furnham, A., 1983. *Social Psychology as Common Sense*, Bulletin of the British Psychological Society 36, 105–109.

Gawel, R. and Godden, P., 2008. *Evaluation of the consistency of wine quality assessments from expert wine tasters*, Australian Journal of Grape and Wine Research 14(1), 1–8.

Gibbs, S., 2018. *Elon Musk drafts in humans after robots slow down Tesla Model 3 production*, The Guardian . [Online] Available at <https://www.theguardian.com/technology/2018/apr/16/elon-musk-humans-robots-slow-down-tesla-model-3-production> [Accessed 24.04.2018].

Gleeson, B., 2013. *The Silo Mentality: How to break down the barriers*, Forbes . [Online] Available at <http://www.forbes.com/sites/brentgleeson/2013/10/02/the-silomentality-how-to-break-down-the-barriers> [Accessed 14.11.2016].

Greenmeier, L., 2016. *Driverless Cars Will Face Moral Dilemmas*, Scientific American . [Online] Available at <https://www.scientificamerican.com/article/driverless-cars-willface-moral-dilemmas> [Accessed 14.11.2016].

Grindley, G. C. and Townsend, V., 1965. *Binocular masking induced by a moving object*, Journal of Experimental Psychology 17(2), 97–109.

Grove, W. M., Zald, D. H., Lebow, B. S., Snitz, B. E. and Nelson, C., 2000. *Clinical Versus Mechanical Prediction: A Meta-Analysis*, Psychological Assessment 12(1), 19–30.

Hammond, K. R., Hamm, R. M., Grassia, J. and Pearson, T., 1987. *Direct comparison of the efficacy of intuitive and analytical cognition in expert judgment*, *in* 'Proceedings of IEEE Transactions on Systems, Man, and Cybernetics', pp. 753–770.

Hartford, T., 2012. *High-frequency trading and the $440m mistake*, BBC Magazine . [Online] Available at <http://www.bbc.com/news/magazine-19214294> [Accessed 13.11.2016].

Hayakawa, S., Costa, A., Foucart, A. and Keysar, B., 2016. *Using a Foreign Language Changes Our Choices*, Trends in Cognitive Sciences 20, 791–793.

Hayakawa, S. and Keysar, B., 2018. *Using a foreign language reduces mental imagery*, Cognition 173, 8–15.

Heine, S. J., Lehman, D. R., Ide, E., Leung, C., Kitayama, S., Takata, T. and Matsumoto, H., 2001. *Divergent Consequences of Success and Failure in Japan and North America: An Investigation of Self-improving Motivations and Malleable Selves*, Journal of Personality and Social Psychology 81(4), 599–615.

Henrich, J., Haine, S. J. and Norenzayan, A., 2010. *The weirdest people in the world?*, Behavioral and Brain Sciences 33, 61–135.

Hiebert, P. G., 1985. *Anthropological Insights for Missionaries*, Baker Book House.

Hirshleifer, D., 2008. *Psychological Bias as a Driver of Financial Regulation*, European Financial Management 14(5), 856–874.

Hofstede, G., 1980. *Culture's Consequences: International Differences in Work-Related Values*, Sage.

Hunt, M., 2016. *'Ugly Animals' Don't Get Much Donations as Cute Ones Do, Study Shows*, Nature World News . [Online] Available at <http://www.natureworldnews.com/articles/33822/20161212/experts-discovered-ugly-animals-dont-much-donations-cute.htm> [Accessed 20.02.2018].

Hyman, I. E., Boss, S. M., Wise, B. M., McKenzie, K. E. and Caggiano, J. M., 2009. *Did you see the unicycling clown? Inattentional blindness while walking and talking on a cell phone*, Applied Cognitive Psychology 24(5), 597–607.

IBM, 2015. *Industry Insights on Analytics*. Private communication at Data Analytics lecture - Metropolia UAS.

Janis, I., 1972. *Victims of Groupthink: a Psychological Study of Foreign-Policy Decisions and Fiascoes*, Houghton Mifflin.

Jarrett, C., 2012. *Why the Left-Brain Right-Brain Myth Will Probably Never Die*, Psychology Today . [Online] Available at <https://www.psychologytoday.com/us/blog/brain-myths/201206/why-the-left-brain-right-brain-myth-will-probably-never-die> [Accessed 15.03.2018].

Johnson, R. C., 2015. *Microsoft, Google Beat Humans at Image Recognition*, EETimes . [Online] <Available at https://www.eetimes.com/document.asp?doc_id=1325712> [Accessed 21.12.2017].

Kachaner, N. and Kunnas, P., 2017. *Always-On Strategy*, BCG . [Online] Available at <https://www.bcg.com/publications/2017/growth-always-on-strategy.aspx> [Accessed 12.05.2017].

Kahneman, D., 2011. *Thinking, Fast and Slow*, Farrar, Straus and Giroux.

Kahneman, D., Resenfield, A. M., Gandhi, L. and Blaser, T., 2016. *Noise: How to Overcome the High, Hidden Cost of Inconsistent Decision Making*, Harvard Business Review . [Online] Available at <https://hbr.org/2016/10/noise> [Accessed 25.04.2018].

Kahneman, D., Slovic, P. and Tversky, A., 1982. *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Kahneman, D. and Tversky, A., 1973. *On the Psychology of Prediction*, Psychological Review 80(4), 237–251.

Kahneman, D. and Tversky, A., 1979. *Prospect theory: An analysis of decisions under risk*, Econometrika 47, 263–291.

Kart, L., 2015. *How to Get Started With Prescriptive Analytics*. [Online] <Available at https://www.gartner.com/doc/3044418/started-prescriptive-analytics> [Accessed 24.04.2018].

Keller, C., Siegrist, M. and Gutscher, H., 2006. *The Role of Affect and Availability Heuristics in Risk Analysis*, Risk Analysis 26(3), 631–639.

Keysar, B., Hayakawa, S. L. and An, S. G., 2012. *The Foreign-Language Effect: Thinking in a Foreign Tongue Reduces Decision Biases*, Psychological Science 23(6), 661–668. PMID: 22517192.

King, R., 2002. *Mini Marketing*, Pelican Publishing Company.

Klein, G., 2007. *Performing a Project Premortem*, Harvard Business Review . [Online] Available at <https://hbr.org/2007/09/performing-a-project-premortem> [Accessed 24.04.2018].

Klein, G. A., 1989. *Recognition-primed decisions*, *in* W. B. Rouse, ed., ‘Advances in man-machine systems research’, Vol. 5, JAI Press, Greenwich, pp. 47–92.

Klein, G. A. and Hoffman, R. R., 1992. *Seeing the invisible: Perpetual-cognitive aspects of expertise*, *in* M. Rabinowitz, ed., ‘Congnitive science foundations of instruction’, Eribaum, NJ, pp. 203–226.

Klein, G. A., Orasanu, J. and Calderwood, R.and Zsambok, C. E., 1993. *Decision making in action: Models and methods*, Praeger.

Klein, G. and Jarosz, J., 2009. *Conditions for Intuitive Expertise: A Failure to Disagree*, American Psychologist 64(6), 515–526.

Klein, G. and Jarosz, J., 2011. *A Naturalistic Study of Insight*, Journal of Cognitive Engineering and Decision Making 5(4), 335–351.

Kruger, J. and Dunning, D., 1999. *Unskilled and Unaware of It: How Difficulties in Recognizing One’s Own Incompetence Lead to Inflated Self-Assessments*, Journal of Personality and Social Psychology 77(6), 1121–1134.

Kurt, C. F. and Snowden, D. J., 2003. *The new dynamics of strategy: Sense-making in a complex and complicated world*, IBM Systems Journal 42(3), 57–74.

Lake, K., 2018. *Stitch Fix□s CEO on Selling Personal Style to the Mass Market*, Harvard Business Review . [Online] Available at <https://hbr.org/2018/05/stitch-fixs-ceo-on-selling-personal-style-to-the-mass-market> [Accessed 26.04.2018].

Lerner, J. S., Li, Y., Valdesolo, P. and Kassam, K., 2015. *Emotion and Decision Making*, Annual Review of Psychology 66, 799–823.

Lewis, R. D., 2006. *When Cultures Collide: Leading Across Cultures*, Nicholas Brealey International.

Lindgaard, G. and Dudek, C., 2002. *High appeal versus high usability: Implications for user satisfaction*, *in* ‘HF2002 Human Factors Conference’.

Liu, M., Breuel, T. and Kautz, K., 2017. *Unsupervised Image-to-Image Translation Networks*, 31st Conference on Neural Information Processing System . [Online] Available at <https://arxiv.org/abs/1703.00848> [Accessed 27.04.2018].

Lock, G., 2016. *Incompetent and Unaware: You don’t know what you don’t know...*, Human in the System . [Online] Available at <https://www.humanfactors.academy/blog/incompetent-and-unaware-you-don-t-know-what-you-don-t-know> [Accessed 15.04.2018].

Loukides, M., 2011. *What is Data Science?*, O’Rilley.

Luchins, A. S., 1942. *Mechanization in problem solving: The effect of Einstellung*, Psychological Monograph 54(2), i–95.

Lukianoff, G. H. and Haidt, J., 2015. *The coddling of the American mind*, The Atlantic . [Online] Available at <https://www.theatlantic.com/magazine/archive/2015/09/the-coddling-of-the-american-mind/399356/> [Accessed 16.12.2017].

Lunsford, A. and Ruszkiewicz, J., 2004. *Everything’s an Argument*, Bedford/St. Martin’s.

MacLeod, C. M., 1991. *Half a century of research on the Stroop effect: an integrative review*, Psychological Bulletin 109(2), 163 – 203.

Mark, G., Gudith, D. and Klocke, U., 2008. *The cost of interrupted work: More speed and stress*, pp. 107–110.

Matias, J. N., 2017. *Bias and Noise: Daniel Kahneman on Errors in Decision-Making*, Medium . [Online] Available at <https://medium.com/@natematias/bias-and-noise-daniel-kahneman-onerrors-in-decision-making-6bc844ff5194> [Accessed 25.04.2018].

McCulloch, W. and Pitts, W. H., 1943. *A logical calculus of the ideas immanent in nervous activity*, Bulletin of Mathematical Biophysics 5, 115–133.

McGurk, H. and MacDonald, J., 1976. *Hearing lips and seeing voices*, Nature 264(5588), 746□8.

Mellers, B., Stone, E., Atanasov, P., Rohrbaugh, N., Metz, S., Ungar, L., Bishop, M., Horowitz, M., Merkle, E. and Tetlock, P., 2015. *The Psychology of Intelligence Analysis: Drivers of Prediction Accuracy in World Politics*, Journal of Experimental Psychology: Applied 21(1), 1–14.

Milham, M., 2003. *Practice-related Effects Demonstrate Complementary Roles Of Anterior Cingulate And Prefrontal Cortices In Attentional Control*, NeuroImage 18(2), 483 – 493.

Mintzberg, H. Lampel, J. and Ahlstrand, B., 2005. *Strategy Safari: A Guided Tour Through The Wilds of Strategic Management*, Free Press.

Moore, D. I. and Healey, P. J., 2008. *The trouble with overconfidence*, Psychological Review 115(2), 502–517.

Müller-Lyer, F. C., 1889. *Optische Urteilstäuschungen*, Archiv für Anatomie und Physiologie Suppl. 2, 263–270.

Nedelkoska, L. and Quintini, G., 2018. *Automation, skills use and training*, 202. [Online] Available at <https://www.oecd-ilibrary.org/content/paper/2e2f4eea-en> [Accessed 24.04.2018].

Neves, J. H. and Hillman, N., 2017. *Student Academic Experience Survey*, Higher Education Academy. [Online] Available at <http://www.hepi.ac.uk/wp-content/uploads/2017/06/2017-Student-Academic-Experience-Survey-Final-Report.pdf> [Accessed 16.12.2017].

Nguyen, A. M., Yosinski, J. and Clune, J., 2014. *Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images*, CoRR abs/1412.1897.

Nichols, T., 2017. *The Death of Expertise*, Oxford University Press.

Nightingale, S. J., Wade, K. A. and Watson, D. G., 2017. *Can people identify original and manipulated photos of real-world scenes?*, Cognitive Research: Principles and Implications 2(1), 30.

Ophir, E., Nass, C. and Wagner, A. D., 2009. *Cognitive control in media multitaskers*, Proceedings of the National Academy of Sciences .

Paul, S., 1969. *Analyzing the expert judge: a descriptive study of a stockbroker's decision process*, Journal of Applied Psychology 53(4), 255.

Perreault, J. Cannon, J. and McCarthy, E. J., 2013. *Basic Marketing: A Marketing Strategy Planning Approach*, McGraw-Hill Education.

Poisson, D. and Larrey, D., 2001. *Statistical research on conditions caused by calculi by Doctor Civiale*, Int J Epidemiol. 30(6), 1246–9.

Ponczek, S., 2018. *Can Humans Understand How Robots Invest?*, Bloomberg Businessweek . [Online] Available at <https://www.bloomberg.com/news/articles/2018-04-10/can-humans-understand-how-robots-invest> [Accessed 24.04.2018].

Pontikes, E. G. and Barnett, W. P., 2017. *The Non-consensus Entrepreneur: Organizational Responses to Vital Events*, Administrative Science Quarterly 62(1), 140–178.

Poundstone, W., 2017. *The Dunning-Kruger President*, Psychology Today . [Online] Available at <https://www.psychologytoday.com/us/blog/head-in-the-cloud/201701/the-dunning-kruger-president> [Accessed 22.04.2018.

Powell, C. S., 2018. *Memory-boosting brain implants are in the works. Would you get one?*, Euronews . [Online] Available at <http://www.euronews.com/2018/04/23/memory-boosting-brain-implants-are-works-would-you-get-one-ncna868476> [Accessed 24.04.2018].

Power, D. J., 2007. *A Brief History of Decision Support Systems*. [Online] Available at <http://DSSResources.COM/history/dsshistory.html> [Accessed 24.11.2017].

Purdy, M. and Daugherty, P., 2017. *How AI boosts industry profits and innovation*, Accenture . [Online] Available at <www.accenture.com/aiboostsprofits> [Accessed 26.04.2018].

PwC, 2010. *What does your reporting say about you?* [Online] <Available at http://pwc.blogs.com/files/what-does-your-reporting-say-about-you.pdf> [Accessed 27.04.2018].

PwC, 2016. *Data and Analytics Survey 2016: Big Decisions*. [Online] Available at <https://www.pwc.com/us/en/analytics/publications/human-factor.html> [Accessed 21.03.2017].

Quaddus, M. and Woodside, A. G., 2015. *Sustaining Competitive Advantage via Business Intelligence, Knowledge, Management, and System Dynamics*, Emerald Group Publishing.

Quine, W. V. and Ulian, J. S., 1970. *The Web of Belief*, McGraw-Hill.

Rasmussen, J., 1983. *Skill, rules and knowledge: Signals, signs, and symbols, and other distinctions in human performance models*, *in* 'Proceedings of IEEE Transactions on Systems, Man, and Cybernetics', pp. 257–266.

Redman, T. C., 2018. *Are You Setting Your Data Scientists Up to Fail?*, Harvard Business Review . [Online] Available at <https://hbr.org/2018/01/are-you-setting-your-data-scientists-up-to-fail> [Accessed 24.04.2018].

Ries, E., 2011. *The Lean Startup*, Portfolio Penguin.

Robbins, S. P., Judge, T. A. and Campbell, T. T., 2010. *Organizational Behaviour*, Pearson Education.

Roese, N. J. and Vohs, K. D., 2012. *Hindsight Bias*, Perspectives on Psychological Science 7(5), 411–426. PMID: 26168501.

Rogers, E., 2003. *Diffusion of Innovations, 5th Edition*, Simon and Schuster.

Samuel, A. L., 1959. *Some Studies in Machine Learning Using the Game of Checkers*, IBM Journal of Research and Development .

Savage, I., 2013. *Comparing the fatality risks in United States transportation across modes and over time*, Research in Transportation Economics 43, 9–22.

Schacter, D. L., Chiao, J. Y. and Mitchell, J. P., 2003. *The Seven Sins of Memory - Implications for Self*, Annals of the New York Academy of Sciences 1001, 226–239.

Schein, E., 1985. *Organisational Culture and Leadership*, Jossey Bass.

Schuppe, J., 2017. *Post Bail*, NBC News . [Online] Available at <https://www.nbcnews.com/specials/bail-reform> [Accessed 24.04.2018].

Searcey, D., 2014. *Marketers are sizing up the Millennials*, The New York Times . [Online] Available at <https://www.nytimes.com/2014/08/22/business/marketers-are-sizing-up-the-millennials-as-the-new-consumer-model.html> [Accessed 27.04.2018].

Segall, M. H., Campbell, D. T. and Herskovits, M. J., 1966. *The influence of culture on visual perception*, Bobbs-Merrill.

Sharda, R. Delen, D. and Turban, E., 2014. *Business Intelligence - A managerial perspective on analytics*, Pearson Education Limited.

Simon, H. A., 1955. *Rational Choice and the Structure of the Environment*, Psychological Review 63, 129–138.

Simon, H. A., 2000. *Bounded rationality in social science: Today and tomorrow*, Mind & Society 1, 25 – 39.

Smith, A., Bernheim, B. D., Camerer, C. and Rangel, A., 2014. *Neural Activity Reveals Preferences Without Choices*, American Economic Journal Microeconomics 6, 1–36.

Snopes, 2016. *Snopes.com Participates in Facebook□s Effort to Combat Hoaxes, Fake News*. [Online] Available at <https://www.snopes.com/news/2016/12/15/snopes-com-facebook-fake-news-initiative> [Accessed 23.04.2018].

Soars, B., 2009. *Driving sales through shoppers’ sense of sound, sight, smell and touch*, International Journal of Retail & Distribution Management 37(3), 286–298.

Solt, M. and Statman, M., 1989. *Good companies, bad stocks*, Journal of Portfolio Management 15, 39–44.

Stanovich, K. E. and West, R. F., 2000. *Individual differences in reasoning: Implications for the rationality debate?*, Behavioral and Brain Sciences 23, 645 – 726.

Stiehm, J., 2010. *U.S. Army War College: Military Education In A Democracy*, Temple University Press.

Stroop, J. R., 1935. *Studies of interference in serial verbal reactions*, Journal of Experimental Psychology 18, 643 – 662.

Su, J., Vargas, D. V. and Sakurai, K., 2017. *One pixel attack for fooling deep neural networks*, CoRR abs/1710.08864.

Sun, L. H. and Eilperin, J., 2017. *CDC gets list of forbidden words: fetus, transgender, diversity*, Washington Post . [Online] Available at <https://www.washingtonpost.com/national/health-science/cdc-gets-list-of-forbidden-words-fetus-transgender-diversity/2017/12/15/f503837a-e1cf-11e7-89e8-edec16379010_story.html> [Accessed 16.12.2017].

Swearingen, J., 2018. *YouTube’s Algorithm Wants You to Watch Conspiracy-Mongering Trash*, New York Magazine . [Online] Available at <http://nymag.com/selectall/2018/02/youtubes-recommendation-algorithm-favors-conspiracy-videos.html> [Accessed 23.04.2018].

Takahashi, K., 2017. *Curvature Blindness Illusion*, I-Perception 6(6).

Tetlock, P. E., Mellers, B. A., Rohrbaugh, N. and Chen, E., 2014. *Forecasting Tournaments: Tools for Increasing Transparency and Improving the Quality of Debate*, Current Directions in Psychological Science 23(4), 290–295.

The Economist, 2015. *The creed of speed*. [Online] <Available at http://www.economist.com/news/briefing/21679448-pace-business-really-getting-quicker-creed-speed> [Accessed 27.04.2018].

The Economist, 2018. *A study finds nearly half of jobs are vulnerable to automation*. [Online] Available at <https://www.economist.com/blogs/graphicdetail/2018/04/daily-chart-15> [Accessed 24.04.2018].

Therriault, A., 2016. *Data and Democracy. How Data Science is Shaping the 2016 Elections*, O'Rilley.

Thielman, S., 2016. *Facebook fires trending team, and algorithm without humans goes crazy*, The Guardian . [Online] Available at <https://www.theguardian.com/technology/2016/aug/29/facebook-fires-trending-topics-team-algorithm> [Accessed 23.04.2018].

Thorndike, E. L., 1920. *A constant error in psychological ratings*, Journal of Applied Psychology 4(1), 25–29.

Tombu, M. N., Asplund, C. L., Dux, P. E., Godwin, D., Martin, J. W. and Marois, R., 2011. *A Unified attentional bottleneck in the human brain*, Proceedings of the National Academy of Sciences of the United States of America 108(33), 13426–13431.

Trompenaars, F. and Hampden-Turner, C., 1997. *Riding the Waves of Culture - Understanding Cultural Diversity in Business*, Nicholas Brealey International.

Tuckman, B. and Jensen, M., 1977. *Stages of Small Group Development*, Group and Organizational Studies 2, 419–427.

Tuckman, B. W., 1965. *Developmental sequence in small groups*, Psychological Bulletin 63(6), 384–399.

Tuk, M. A., Trampe, D. and Warlop, L., 2011. *Inhibitory Spillover: Increased Urination Urgency Facilitates Impulse Control in Unrelated Domains*, Psychological Science 22(5), 627–633.

Turing, A., 1950. *Computing machinery and intelligence*, Mind 5(236), 433–460.

Tusche, A., Bode, S. and Haynes, J., 2010. *Neural Responses to Unattended Products Predict Later Consumer Choices*, Journal of Neuroscience 30(23), 8024–8031.

Tversky, A. and Kahneman, D., 1974. *Judgment under Uncertainty: Heuristics and Biases*, Science 185(4157), 1124–1131.

van Doorn, J., Verhoef, P. C. and Bijmolt, T. H. A., 2007. *The importance of non-linear relationships between attitude and behaviour in policy research*, Journal of Consumer Policy 30(2), 75–90.

Vance, A., 2017. *Elon Musk: How the Billionaire CEO of SpaceX and Tesla is Shaping our Future*, Ecco.

Vaughan, D., 1997. *The Challenger Launch Decision*, University of Chicago Press.

Vincent, J., 2016. *Twitter taught Microsoft AI chatbot to be a racist asshole in less than a day*, The Verge . [Online] Available at <https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist> [Accessed 23.04.2018].

Wason , P., 1960. *On the failure to eliminate hypotheses in a conceptual task*, Quarterly Journal of Experimental Psychology 12(3), 129–140.

Weinschenk, S., 2012. *The True Cost Of Multi-Tasking*, Psychology Today . [Online] Available at <https://www.psychologytoday.com/us/blog/brain-wise/201209/the-true-cost-multi-tasking> [Accessed 14.03.2018].

Xu, A. J., Schwarz, N. and Wyer, R. S., 2015. *Hunger promotes acquisition of nonfood objects*, Proceedings of the National Academy of Sciences 112(9), 2688–2692.

Yates, J. F., Veinott, E. S. and Patalano, A. L., 2003. *Hard decisions, bad decisions: On decision quality and decision aiding*, *in* S. L. Schneider and J. Shanteau, eds, 'Emerging perspectives on judgment and decision research', Cambridge University Press, New York, pp. 13–63.

Zhao, J., Wang, T., Yatskar, M., Ordonez, V. and Chang, K., 2017. *Men Also Like Shopping: Reducing Gender Bias Amplification using Corpus-level Constraints*, *in* 'Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing', pp. 2979–2989.