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DECAS: a modern data-driven decision theory for big data and analytics

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ABSTRACT
Decisions continue to be important to researchers, organizations and societies. However, decision research requires re-orientation to attain the future of data-driven decision making, accommodating such emerging topics and information technologies as big data, analytics, machine learning, and automated decisions. Accordingly, there is a dire need for re-forming decision theories to encompass the new phenomena. This paper proposes a modern data-driven decision theory, DECAS, which extends upon classical decision theory by proposing three main claims: (1) (big) data and analytics (machine) should be considered as separate elements; (2) collaboration between the (human) decision maker and the analytics (machine) can result in a collaborative rationality, extending beyond the classically defined bounded rationality; and (3) meaningful integration of the classical decision making elements with data and analytics can lead to more informed, and possibly better, decisions. This paper elaborates the DECAS theory and clarifies the idea in relation to examples of data-driven decisions.

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Data-driven decision making; big data; analytics; automated decisions; decision theory; algorithmic decisions

1. Introduction

Decisions have always been the foundation of organisational performance and competitiveness. Many successes and failures throughout the years have been attributed to a single, fate-changing decision. Accordingly, a massive pressure has been placed upon decision makers to ensure that the best achievable decision is made in a timely manner (Bartkus et al., 2018). From how decisions were/are made, to the characteristics defining decision makers and decision-making processes, to methods and techniques on how, or on whether it is even possible, to reach the optimal decision; decision making has never ceased to attract research interest. This has led to a plethora of research in decision-making and decision theory throughout the twentieth century. Through a convergence of intellectual disciplines such as mathematics, sociology, psychology, economics and political science, philosophers and theorists have pondered what decisions say about people and their values, and how they can be explained and enhanced. Accordingly, research ensued in organisational behaviour and decision making, risk, uncertainty, complexity,

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rationality, optimisation, decision aids and decision support tools, etc. Along with a more nuanced understanding of human behaviour and advances in technology that support and mimic cognitive processes, this has led to improved decision making in many situations (Buchanan & O'Connell, 2006).

Around the mid-twentieth century, research started to document decision systems, including decisions by people along with machines with good predictive power. This sparked a new interest in decision systems in terms of people, processes, systems, and data for making decisions or supporting decision processes (Power, Heavin, et al., 2019). Moreover, with the advancements in data science, machine learning, big data, and analytics, data-driven decision making, or making decisions based on the results and evidence provided by analytics, has gained popularity. Hence, data-driven decision making has recently been perceived as a solution for providing more informed, quality decisions which combine the intuition and experience of human decision makers with the analysis of data, thus providing more rational choices leading to better results (Janssen et al., 2017; Power, 2016; Provost & Fawcett, 2013).

The power of harnessing big data and the growing interest in big data analytics (BDA) has also added to the hype by promising enhanced decision making through utilising the capabilities of humans and machines, and their combined interaction (P. Grover & Kar, 2017; Gupta et al., 2018). With the increasing variety and volume of data which can be combined and analysed, such as social media data, etc., different analytical approaches and methods in multiple industrial domains have gained interest in research, with the ultimate goal and potential for enhancing decision making. This has enabled more collaborative decision-making processes through inputs emerging from different information sources, and the application of advanced analytics (Rathore et al., 2017).

Furthermore, the flourishing coexistence of artificial intelligence (AI) supported systems with human decision makers in organisations has further ignited an interest in synergistically augmenting their intelligence and capabilities, leading to more 'intelligent' data analysis, and consequently supporting and enhancing decision making (P. Grover et al., 2020; Kotsiantis et al., 2006). This collaboration has led to different dimensions of intelligence and a range of applications from less to more complex, with the aim of best combining human and machine capabilities for better data-driven decision making, depending on the environment and the type of decision (Trunk et al., 2020).

Hence, from supporting human decision makers, to fully automating decision processes, the reliance on technology as a major part of organisational decision making has increased. However, despite the growing amount of data, tools, and insights, decision makers are still not fully harnessing the power of current technologies, especially without clearly defined guidelines and processes, which still requires further research (Power, Cyphert, et al., 2019; P. Grover et al., 2020).

1.1. Motivation and aim

In 2019, AlgorithmWatch published a report on automated decision making in the EU. This extensive report described numerous cases of governments and organisations in each EU country which had either implemented, were implementing, or were studying the implications and implementation of data-driven decision making. Accordingly, this report provides insight into the importance of data-driven decision making and its application, and the need for considerable research in the future of decisions. However, data-driven decisions are still failing, regardless of the bountiful promises of technology, automation, and AI, and the reasons why need to be studied and addressed. For example, Ioannidis et al. (2020) conveyed how decisions based on COVID-19 forecasting have failed, partly due to poor data input, wrong modelling assumptions, poor past evidence, lack of transparency, errors, and considering only a few dimensions of the problem at hand.

On the other hand, Bean and Davenport (2019) argued that companies are failing to become data-driven, based on the alarming results of NewVantage Partners' (NewVantage Partners, 2019) 'Big Data and AI Executive Survey', whose participants included 64 c-level technology and business executives representing very large corporations. It was made clear that there is still an eminent need for data-driven cultures, where data is treated as an important business asset which receives more attention, investments, and resources.

Frisk and Bannister (2017) also highlighted that although the skilful use of data analytics and big data can radically improve a company's performance, managers need to change their decision-making culture in order to be able to achieve such improvements. Their case studies on three public fire and rescue service organisations in Sweden showed a structural problem in the way decisions were driven. Although having a strong technology focus, decisions were taken in silos, there was little to no involvement of the users, and IT was not realised as a strategic resource. Accordingly, there was too much focus on the technology when investing in costly ICT systems and services, but too little focus on how they affect the business and organisational decision making, as well as on the total picture. Therefore, the incorporation of big data and analytics requires moving towards a more considered and systematic form of data-driven decision making.

Consequently, poor decisions require learning from the past in order to guide decision makers away from failure-prone practices (Nutt, 2010). As shown in a recent research report from MIT Sloan, organisational learning requires humans and machines to not only work together, but also to learn from each other, share growing collective knowledge between humans and AI through digital data and human experience, and utilise data, technology and algorithms. However, this requires significant change and effort, as well as deliberating the degree of human and machine interaction, depending on the scenario and type of decision (Ransbotham et al., 2020).

Current research has highlighted the importance of big data, analytics, and AI in decision making, as well as their implications on decision factors, such as quality, efficiency and success. However, such research, while inevitably tackling important individual opportunities and challenges, has not provided an overall theory of data-driven decision making which encompasses the parts altogether. Furthermore, although the decision-making approaches, methods, and theories of renowned scholars, such as Herbert Simon and Henry Mintzberg, have successfully withstood countless tests of time and applicability, every era requires the addition of modern approaches to current theories in order to support environmental changes and technological advancements. The best that a large part of current information systems (IS) research has done in recent data-driven decision-making topics, is synonymous to forcing a square peg into a round hole, by having to accept the application of existing theories, and abstractly compelling them to explain what they cannot with the current technological advancements.

While solutions and explanations have been explored for individual concepts and phenomena of data-driven decision making, a comprehensive theory which builds on the scientifically sound principles of classical decision theory, while encompassing and capturing the interrelationship between all the elements, has not been suggested. Therefore, the aim of this research is to address the discerning lack of existing theory in accommodating the modern elements of data-driven decision making. Hence, the research question is: *'How can we add to classical decision theory in order to support data-driven decision making with (big) data and analytics?'*

1.2. Research method

Accordingly, the purpose of this research is to answer the research question by exploring the literature in order to develop a decision theory, which accommodates for the capabilities of data-driven decision making by integrating the classical decision-making elements with the modern advancements in big data and data analytics. This theory aims to serve as an epistemological baseline for supporting the endeavours of data-driven decision making, providing explanations beyond classical theory, and hence enabling future research in the field. In order to avoid traditional gap-spotting researching, and to rather conduct innovative path-(up)setting research, the theory is developed using Alvesson and Sandberg's (Alvesson & Sandberg, 2013) 'problematisation as a methodology' for assumption challenging studies. This requires following six methodological principles, which are: (1) identifying a domain of literature, (2) identifying and articulating assumptions underlying the domain, (3) evaluating the assumptions, (4) developing an alternative assumption ground, (5) considering it in relation to its audience, and finally (6) evaluating the alternative assumption ground. The process is depicted in Figure 1.

Consequently, the paper starts with an analysis of the literature and a theoretical background on the relevant concepts and theories related to traditional decision theory, as well as big data, analytics, and data-driven decision making (identifying the domain and the underlying assumptions). Due to the multidisciplinary nature of the topic, it is important to ground it in quality decision-making research as a theoretical foundation (Arnott & Pervan, 2008). The paper then moves on to discuss the need for a new theory, both in IS research and then in practice, by highlighting examples of data-driven decision making where the shortcomings are inexplicable with current decision theories (evaluating the assumptions of classical decision theories). Consequently, DECAS, which encompasses the Decision-making process, dEcision maker, deCision, dAta and analyticS, is proposed as a modern data-driven decision theory and explained in detail, using Toulmin's (2003) argumentation model as a means of representation in order to portray the claims according to Gregor's (2006) structural components of a theory (developing an alternative assumption ground and considering it in relation to its audience). Subsequently, the theory is discussed in regard to the data-driven decision-making scenarios portrayed throughout the paper, as well as relevant research and works which further support the claims (evaluating the alternative assumption ground). Finally, the paper ends with a conclusion and suggestions for future work.

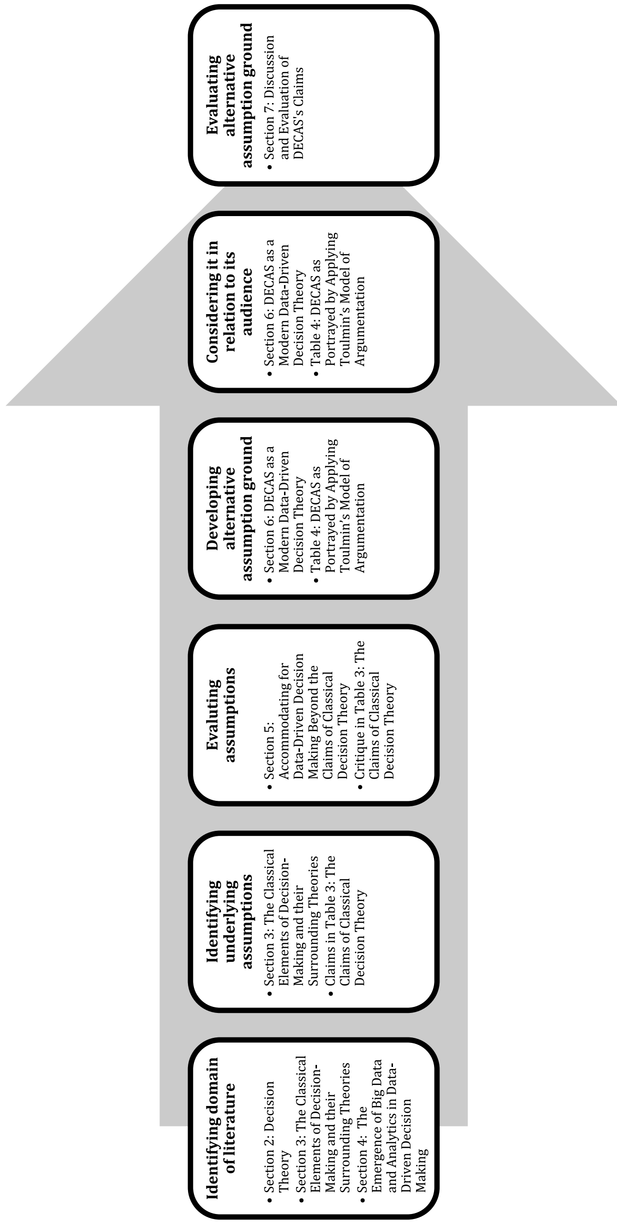

Figure 1. The 'problematisation as a methodology' research process.

2. Decision theory

Decision theory, simply put, is the study of choices in order to make a decision. However, decisions are far from simple, and their surrounding theories have been complex subjects of focus and debate throughout many decades of interdisciplinary research (Hansson, 1994). Moreover, decision theory has primarily focused on rational decision making (Peterson, 2011). It is a systematic study of the goal-directed, non-random behaviours and actions of decision makers, under events or conditions when different options or courses of action can be chosen (Hansson, 1994). Hence, the decision problem is the situation in which a decision maker chooses what to do from a set of alternative acts, which are affected by events taking place outside of the decision maker's control, and accordingly result in various outcomes with positive or negative payoffs (Peterson, 2011). Accordingly, decision theory usually focuses on the outcome of decisions as judged by pre-determined criteria or on means-ends rationality (Hansson, 2011).

Furthermore, decision theories are usually described as normative or descriptive. Normative decision theory seeks to yield prescriptions about what decision makers ought to, or are rationally required, to do (Peterson, 2011). Accordingly, a normative decision theory is a theory about how decisions should be made, or the prerequisites which should exist to reach rational decision making (Hansson, 1994). However, psychologists and economists, including Nobel Prize winner Herbert Simon, criticised the assumptions about the human decision maker in the rational theory, describing it as unfounded and psychologically unrealistic, calling for alternative theories (Gigerenzer & Gaissmaier, 2015). Accordingly, recent advances in the psychology of intuitive judgement and choice have differentiated between separate cognitive systems requiring different models and explanations than the formal normative and rational models known before (Kahneman, 2003).

On the other hand, descriptive decision theory is an empirical discipline which seeks to explain and predict how people actually make decisions (Peterson, 2011). The starting point for descriptive decision theories came from empirical experiments where it was shown that people's behaviour was inconsistent with the normative theories. It is concerned with how and why people think and act the way they do, without trying to modify, influence, or moralise about such behaviour. Descriptive decision theory also assumes that decisions in real life can be non-rational as well as rational (Bell et al., 1988). Thus, descriptive and normative decision theories are, two separate fields, which may or may not interrelate (Peterson, 2011).

With the emergence of AI and new technologies, research has aimed to extend the principles of decision theory, along with information theory, game theory, systems theory, etc., by applying them to 'intelligent' agents and machines. The focus has been on the decision-making processes of machines, and how they can be 'trained' or 'taught' to 'decide'. Simon's (1977) view on AI was that both human thinking and information processing programs were similar in that they scan data for patterns, store the patterns in memory, and then apply the patterns to make inferences or extrapolations. Consequently, some programs can reproduce or even surpass human decision-making or problem-solving capabilities (Frantz, 2003). However, the extent of collaboration between both, and the consequential effect on decision making still need to be further examined.

Moreover, while classical decision theories rely on a numerical representation of a decision process, the requirement of numerical concepts is sometimes too difficult in real life (Graboś, 2004). Although remarkable, the tools of traditional decision theory have not proven fully adequate for supporting attempts to automate decision making in the field of AI, in more complicated and realistic cases with unforeseen preferences or decision choices, or in cases where the underlying assumptions are susceptible to change (Doyle & Thomason, 1999).

This has motivated the work on various frameworks and functions in AI, and led to a focus on a qualitative representation of decision making, or qualitative decision theories (Graboś, 2004). Qualitative decision theories aim to provide better support for automation by developing qualitative and hybrid representations and procedures that both complement and improve the quantitative decision theory's ability to address the full range of decision-making tasks (Doyle & Thomason, 1999). Unfortunately, as decision theory is an entire field and study of its own, this research only focuses on a few relevant aspects.

3. The classical elements of decision making and their surrounding theories

Decision making has been a topic widely studied for centuries. While the types of decisions and decision makers in question differ, continuous research on the who, where, what, when, why, and how of decision making has never ceased to exist. However, the focus of this paper is limited in scope to the twentieth-century Euro-American classical decision theories, due to their prominence in management, organisational decision-making, 'thinking machines', and decision support systems. This includes the work of researchers and theorists such as Simon, Mintzberg, March, Drucker and many others who laid such foundations (Buchanan & O'Connell, 2006). Accordingly, the main elements around which the majority of such research revolves can be distinguished as the decision-making process, the decision maker, and the decision itself. These elements, summarised in Figure 2, along with some of the relevant surrounding concepts are discussed in the following subsections.

3.1. The decision-making process

Depending on the complexity of the decision problem, the decision-making processes, or the processes adopted and followed by organisations in order to reach a decision, may be structured or unstructured (Langley et al., 1995). Simon followed a structured approach and stated that the decision-making process is sequential, and involves intelligence, design, choice and review or implementation. Intelligence is gathering the data and information related to the decision, while design is analysing the alternatives to determine the possible outcomes and look at how they will meet the goals. Accordingly, good choices will be more difficult to make if either of these phases are neglected. Finally, a choice between the possible alternatives is made (Frisk & Bannister, 2017; Pomerol & Adam, 2004).

Drucker (1967) also argued that an effective decision is made through a systematic process with clearly defined elements and a structured sequence of steps. The proposed steps start with classifying the problem whether it is generic or unique, then defining the problem, specifying the answer to the problem and the boundary conditions, deciding as

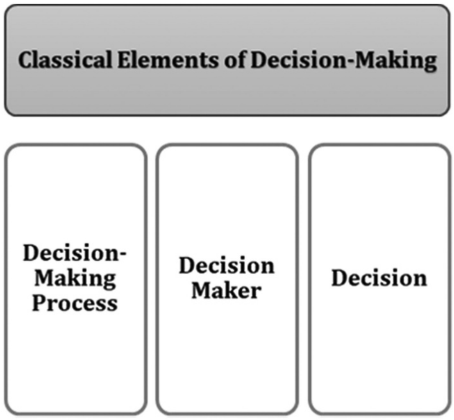

Figure 2. The elements of classical decision making.

to what is right, rather than what is acceptable in order to meet the boundary conditions, converting the decision into action, and finally evaluating the decision by testing its validity and effectiveness against the actual course of events.

On the other hand, unstructured decisions refer to decision processes which have not previously been encountered and for which no predetermined and explicit set of ordered responses exists (Intezari & Gressel, 2017). Mintzberg and Westley (2001) argued that decision making is not always a thinking first or a linear process. Accordingly, they suggested that the rational decision-making process is iterative and is identified as follows: define, diagnose, design, decide. The main goal of decision making is to be rational by collecting the relevant information regarding the problem or issues requiring investigation, followed by generating all possible alternatives and examining the resulting consequences, and finalised by choosing the most optimal alternative (Kalantari, 2010). However, the rational approach proves to be uncommon in several scenarios, and thus rationality should not be the only focus of the decision-making process (Mintzberg & Westley, 2001). Moreover, in cases where decision problems are vague, uncertain and fuzzy, or for which no pre-defined process and optimal solution exists, sometimes human intuition, experience and judgement can be the basis for decision making. Accordingly, decision making does not always follow clearly structured or pre-defined phases but can rather sometimes be based on a combination of data, experience and feeling. Furthermore, depending on the decision circumstances, the time frame, the strategies adopted by the organisation, and the level of the impact of the decision consequences, the importance of each phase in the decision-making process may vary (Intezari & Gressel, 2017).

3.2. The decision maker

The decision maker is the person who applies the decision-making process to reach a decision. It is up to the decision maker to have full and current information upon which to base the decision (Mintzberg, 1975). Simon (1997) argued that decision makers cannot be rational, since they do not have perfect control over the environmental factors as well as their mental capabilities. Therefore, he believed that due to the disparity between the complexity of the world and the fitness of human computational capabilities, limitations on human rationality and calculation will continue to exist, even with or without computers (Kalantari, 2010).

Hence, the term 'bounded rationality' was used to define the assumption that rationality in humans, was at least in some important respects, bounded by human computational limits (Simon, 1997). The decision maker when faced by a choice, selects the first solution considered as satisfactory without trying to attain an unrealistic (and maybe useless) optimal solution. Furthermore, Simon considered decision theory to assume that decision makers always know the problem on hand, that they can formulate the problem as an effectiveness or efficiency problem, and that they have the necessary information and resources available to always find a solution. However, he argued that is never true in reality. Thus, decision makers never have a precise idea of their problem, the problems can rather be formulated as a search for a satisfying compromise, and a solution for the problem is always constrained by time and available resources (Tsoukiàs, 2008). Consequently, it is up to a good decision maker to be able make decisions using any of the decision-making processes depending on the situation (Kalantari, 2010).

Moreover, classical theory assumes that the decision maker chooses among fixed and known alternatives, of which each has known consequences. However, this is no longer accurate once human perception and cognition intervene between the decision maker and the environment. Contrarily, in the choice process, alternatives are not given, but should rather be sought, and the determination of consequences is a tedious and difficult task, especially since the decision maker's information about the environment is much less than a perceived approximation of the actual state of the environment (Simon, 1959).

Furthermore, Simon pointed out that since computers solve problems using heuristics and means–end analysis (at the time), similar to humans, then they can be considered to 'think' and display intelligence, or behaviour appropriate to the goal and adaptive to the environment. Such intelligence allows the limited processing capacity of the decision maker, whether man or machine, to use efficient search procedures to generate possible solutions (Frantz, 2003). Consequently, Simon (1959) claimed that if the decision premises can be translated into computer terminology, then the digital computer can provide us with an instrument for simulating even very complex human decision processes.

Nevertheless, humans and machines are not the same, and a distinction needs to be made between both. And while computers have much evolved since then and do not solve problems in the same way anymore, even in Simon's definitions AI is an enabler, and is an instrument or tool for simulating or aiding decision making. However, it does not replace the human decision maker, who has received so much attention in decision theory research. Mintzberg (1989) further elucidates the importance of the decision maker's role and argued that while the computer is important for supporting specialised work, the human decision maker's role continues to be the same.

3.3. The decision

Finally, the decision is the result of the decision maker going through the decision-making process and selecting the best alternative. However, since the decision maker is limited by cognitive abilities and external factors, or with bounded rationality, the optimal decision cannot be reached. Consequently, the decision maker constructs a simplified model of rationality, taking into consideration the surrounding limitations, in order to be able to deal with the circumstances and search for a satisfactory, or good enough, decision. Such decisions are described as 'satisficing' (Kalantari, 2010; Pomerol & Adam, 2004). Accordingly, research continues to search for ways to reach, or at least come closer to reaching, the so far unreachable 'optimal' decision.

However, since the classical model of rationality assumes knowledge of the relevant alternatives, consequences, probabilities, and a predictable world without surprises, it is important to differentiate between these perfect knowledge small worlds and other, more common, large worlds. In such cases, part of the relevant information is unknown or must be estimated, so the conditions for rational decision theory are not met, making it inappropriate for optimal reasoning and requiring different theories, heuristics, and expectations for the range of situations (Gigerenzer & Gaissmaier, 2011).

Moreover, another important characteristic of the decision is its quality. The decision quality includes timeliness, accuracy and correctness of the decision (Janssen et al., 2017). For quantitative decisions, validity and reliability are also considered characteristics of quality (Ho, 2017). Previous research about the use of data shows that the data quality influences the decision quality. Furthermore, the decision quality depends not only on the data itself, but also on the process in which the data is collected and the way it is processed (Janssen et al., 2017).

As technology has evolved throughout the years, the way decisions are made has gone through considerable transformation. From being based purely in the human mind, to benefiting from the supporting computational power and simple analyses of computers, to relying completely on machines and algorithms in automating decisions, or to being enhanced by the use of analytics in order to extract hidden insights from vast amounts of data and see what could not have been perceived before; decisions have inevitably changed.

4. The emergence of big data and analytics in data-driven decision making

One inherited concept from classical literature that will always stand true, is Mintzberg's (1989) statement that information 'is the basic input to decision-making'. However, the information available has inevitably evolved throughout the years. Back then, it was only the manager that had the full and current information to make the set of decisions, and information was mainly sought by word-of-mouth and data was mostly verbal (Hansson, 1994; Mintzberg, 1989). With the reliance on technology and machines, and the increasing amounts of data available on hand, big data and BDA have gained popular interest throughout recent years. They are briefly discussed below, followed by the concept of data-driven decision making, which utilises the information, patterns, and insights provided by the analytics to reach more informed decisions supported by facts and data.

4.1. Big data

First of all, big data is data that cannot be handled using traditional tools and techniques due to its high volume, variety, velocity, value, and veracity (Elgendy & Elragal, 2014). Volume is the sheer size or the quantity of the data, while variety refers to the different types of data collected from structured and unstructured data sources. Velocity means the speed of collection, processing or updating and analysing of the data. On the other hand, value refers to the strategic and informational benefits of big data, and veracity represents the reliability of the data sources. In recent years, variability and visualisation have also been added. Variability refers to how the insights constantly change as the interpretation of information changes, or as the addition of new data changes the outcome. Finally, visualisation is the representation of data and hidden patterns and trends in meaningful ways (Mikalef et al., 2018).

Nevertheless, traditional tools are not able to address the issues of scalability, adaptability, and usability necessary for big data (Saggi & Jain, 2018). This is because big data involves not only the ability to handle large volumes of data, but also represents a wide range of analytical capabilities and business possibilities. It enables automated real-time actions, and intraday decision making. Therefore, it requires new forms of processing in order to enable enhanced decision making, insight discovery, and process optimisation (Mikalef et al., 2018). Kamioka and Tapanainen (2014) also described big data as large-scale data with various sources and structures, which is intended for organisational or societal problem solving, and accordingly cannot be processed by traditional methods. Due to the heterogenous and autonomous resources, complex and dynamic relationships, diversity in dimensions, and size, big data is beyond the capacity of conventional tools or processes to effectively capture, store, manage, analyse, or exploit (Mikalef et al., 2018).

Furthermore, big data can unlock significant value by making more types of information transparent and usable at a higher frequency, enhancing the development of products and services, boosting performance, improving decision making, and leading to better and more informed management decisions (Manyika et al., 2011). However, it requires the proper technology, computational power, and algorithmic accuracy to gather, analyse, link, and compare such datasets. As a result, big data can offer a higher form of intelligence and knowledge that can generate insights which were previously impossible, with the impression of truth, objectivity, and accuracy (Boyd & Crawford, 2012). Nevertheless, the mere possession of big data is not enough to yield sustainable competitive advantage, which rather necessitates the ability to assemble structured and unstructured data, analyse vast amounts of such data, and utilise the insights to inform decisions (Amankwah-Amoah & Adomako, 2019).

Moreover, a variety of data emerges from different sources and devices, and the velocity and volume of data generated within organisations fluctuates to a large extent which requires utilising analytics to enhance functional flexibility and agility. Nevertheless, when data is created at such a high pace in flexible organisation systems, especially if the data is in siloes, it often contains noise, biases, outliers and abnormalities which need to be cleaned and processed before improved and generalisable decision making can be enabled. On the other hand, such data if properly handled and analysed, can generate value for organisations, convey the potential for more extensive insight, and leverage the decision-making process. Thus, the information gained can be used for making better data-driven decisions, while maintaining flexibility and agility. However, due to the difficulty of analysing big data, a revolutionary step is needed from traditional data analysis (P. Grover & Kar, 2017).

Accordingly, it is well acclaimed in literature that big data differs from traditional data and requires different methods for storage, management and processing than the data and information available in the past. It is also extensively noted that big data has a direct and positive impact on decision making, and thus is worthwhile to be included in modern-day decision research. Hence, comes the need for BDA.

4.2. Big data analytics

BDA is a holistic approach to managing, processing, and analysing big data sets by applying advanced analytics techniques. It allows for the creation of actionable ideas for measuring performance, establishing competitive advantages, and serving as a new platform for productivity, innovation and improved data-driven decision making (Wamba et al., 2017). Moreover, BDA includes the technologies, processes, tools and techniques or analytical methods, which can be applied to data in order to provide meaningful insights and actionable prescriptive, descriptive and predictive results (Mikalef et al., 2018).

Analytics on big data samples can help reveal and leverage business change. Accordingly, decision making can be substantially improved through sophisticated analytics and valuable insights, which would have otherwise remained hidden, can be extracted (Elgendy & Elragal, 2016). Additionally, BDA can strengthen areas of organisational challenge, such as managing multiple data sources, prediction and optimisation models, and decision making (P. Grover & Kar, 2017). Saggi and Jain (2018) described BDA as a technology-driven ecosystem, which helps extract knowledge from data in an interpretable and appropriate form, and lead to better decision making and informed decisions. Moreover, it can improve operational performance by allowing real-time decision making, enhance data quality and diagnosticity, and consequently lead to better decision making (Jha et al., 2020).

Meanwhile, in order to generate a deep understanding and useful insights from BDA for value creation, there are immense challenges in terms of data, processes, analytical modelling, and management for different applications. Gupta et al. (2018) suggested that there are four main characteristics of decision making with BDA, utilising the capabilities of humans, machines, and their combined interaction. These characteristics are observation, interpretation, evaluation and decision making. The observation of the big data is where aggregation, integration and examination of the data takes place. Next, the interpretation of the datasets provides a better understanding and solving of complex problems when there is a variety of information sources. Evaluation of the data to generate information requires processing huge amounts of data within a short time frame, and also necessitates efficacy in the data analysis in order for the evaluation to be trustworthy and accurate. Finally, the decision is made based on the data which has been analysed. Accordingly, BDA should not be considered synonymous with classical analytics methods and techniques performed on data collected through traditional means and sources.

Consequently, the need arises for a focus on decision making leveraged by big data and analytics, hence interchangeably defined in literature as data-driven, evidence-driven, fact-driven, AI-based, algorithmic decision making, or even automated decision making, as the decision-making task is being delegated – partially or fully – to machines relying on analytics. In this research, the term data-driven decision making is used to refer to such concepts, and is covered in the following subsection.

4.3. Data-driven decision making and its elements

Data-driven decision making refers to the systematic collection, analysis, examination, and interpretation of data, usually through the application of analytics or machine learning methods and techniques, to reach informed decisions (Mandinach, 2012). While the automation of decisions remains debatable, they can at least be augmented through the utilisation of big data techniques and technologies by analysing huge integrated datasets instead of smaller samples (Elgendy & Elragal, 2014). Accordingly, data-driven decision making bases decisions on a combination of the intuition and experience of the decision maker with the analysis of data (Provost & Fawcett, 2013).

Drawing on Simon's approach, the data-driven decision-making process starts with identifying problems and opportunities, then defining strategic objectives and criteria for success, followed by developing and evaluating alternatives, and finally prioritising and selecting one or more of these alternatives. However, in each step, big data technologies, analytics, and machines are essential, since they enable the effective capturing, integration, and analysis of data, which in turn improves the accuracy, sophistication, and completeness of the rational analysis and final decision (Cao & Duan, 2015). Moreover, analysing the large volumes of data, whether internal or external, may create descriptive value, by summarisation of the data and describing current or historic events, predictive value, through predictions about the future based on historic data, and/or prescriptive value, by suggesting optimised courses of action and descriptions of the consequences (Strand & Syberfeldt, 2020). Additionally, data-driven decision making is said to lead to more informed, quality decisions, since more knowledge about the data, the analytics, the relationships among variables, and the resulting information all add to enhancing the decision quality (Janssen et al., 2017).

Furthermore, data-driven decision making can help address the bounded rationality problems discussed by Simon (1997) that refer to the constraints of the cognitive capabilities of the human mind, and the lack of available information or the inability to process vast amounts of such information in order to be able to reach an optimal decision. So while analytics do not necessarily make strategic or high-level decisions, but rather atomic decisions that prioritise, classify, associate, and filter, their output can be used as input for decision makers to make better decisions based on the availability of newfound information and relationships (Cao & Duan, 2015; Diakopoulos, 2016). Moreover, if decision makers act upon the recommendations, then analytics and computerised decision support can potentially help people make rational choices that are more likely to lead to goal attainment and good results (Power, 2016).

Hence, as portrayed in Figure 3, it is concluded that modern data-driven decision making is based upon data and analytics, along with the three previously discussed elements of classical decision making, and accordingly there arises an important set of

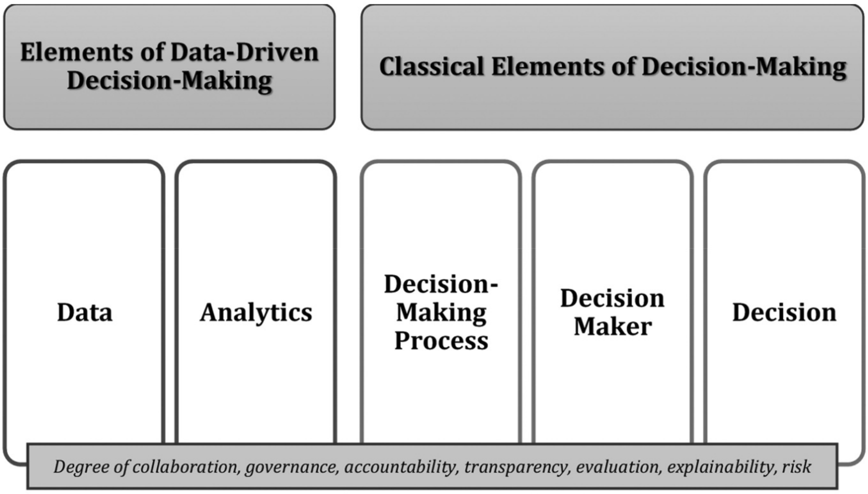

Figure 3. The elements of data-driven decision making.

questions and considerations, such as the degree of collaboration, accountability, transparency, evaluation, explainability, etc. This is the basis for deriving a modern data-driven decision theory, which is discussed in the following section.

5. Accommodating for data-driven decision making beyond the claims of classical decision theory

With the modern advancements in technology, the emergence of big data, analytics and AI, and the focus on data-driven and automated processes, the need for a new theory for decision making under these circumstances arises. While the essence of data-driven decision making is, as with most decision-related topics, based on classical decision theory, it has evolved beyond the capabilities of the past and calls for new approaches in theory to support the future of scientific research in the field. Hence, after perusing the literature, a modern data-driven decision theory has been developed. Accordingly, this theory aims to support decision makers in the digital environments characteristic of nowadays, to reach more informed, optimal, data-driven decisions. The need for developing the theory in research is discussed below, followed by the need in practice. This is emphasised by challenging the assumptions of classical decision theories in supporting data-driven decision making, by evaluating their shortcomings in explaining the data-driven successes and failures of example cases.

5.1. The need for a new theory in research

Theories, methods, and practices have guided scientific research for centuries. Although most of these continue to be used, and have proven their empirical success and sufficiency throughout time and under various circumstances, many need to be updated or evolved in order to accommodate for new technologies and developments. Furthermore, a need for the development of different types of good theories in IS literature and research continues to exist, as the field struggles with the dearth of original and bold theorising, and hence requires novel, genuine, high-level theories around conceptual relationships between information technology, information and social behaviours (Gregor, 2006; V. Grover & Lyytinen, 2015).

In their seminal work, Hassan and Mingers (2018) reinterpreted the(ir) understanding of the Kuhnian paradigm in order to use such (new) understanding to encourage and motivate novelty in conducting research in IS. They explained the need for IS, as a discipline, to have new theories and depart away from being an excessive borrower discipline or from conducting research which is mainly focused on gap-spotting. Contrarily, what holds the IS field together is a sociotechnical axis of cohesion centred on the interplay between the technical or information-related, world and the social world, which provides the opportunity for IS research to be established as a reference field in relation to other social science fields (V. Grover et al., 2020). Accordingly, there is a need for path-(up)setting research which challenges the assumptions underlying the existing literature to develop more interesting and influential theories (Alvesson & Sandberg, 2013).

Lyytinen and Grover (2017) showed that IS theories need to be adapted according to the current situation by revisiting Ackoff's classic 'Management Misinformation Systems' and its five myths (which has been deemed an essence of IS literature for years) in light of today's information and data rich environments, and portraying a new view of the long withheld arguments and assumptions. For example, they added to Ackoff's information overload concept and the argument that managers are faced with an overabundance of relevant information and must filter the relevant from the irrelevant information with a contemporary view. This view states that with the overabundance of data nowadays, and the emergence of data analytics techniques, relevant information is no longer a result of filtering, but rather a process of discovery by combining analytics, visualisation and critical thinking. In response to other arguments, they also added that BDA improves decision making at a different scale and offer new ways to learn from and improve past decisions. Hence, traditional views were not discarded, but rather built upon and adapted to meet present needs.

Traditional decision theory is limited in many cases in guiding decision-making activities, and is subpar in effectively representing and reasoning about decisions which involve a broad knowledge of the world, as well as in communicating about the reasons for decisions in ways intelligible for human decision makers. This accordingly limits the use of traditional decision theories in the automation of decisions, which would require taking qualitative goals, methods and preferences into account, as well as basing decisions on theoretic and analytic information rather than ad hoc rules (Doyle & Thomason, 1999).

Elragal and Klischewski (2017) argued that in order for BDA research to be useful in the long run, it needs to be theory-driven, not only driven by data which is easily available, and accordingly needs epistemological reflection. Since big data and analytics have become the new research hype, their contribution to science cannot be ignored by simply questioning the validity and reliability of big data research. However, the lack of theories and formal methods governing the field conceivably leads to a widespread debate about the empirical accuracy of the findings. As BDA research will inevitably continue to flourish, there is a growing need for developing more theories and methods to support research in the field.

This is further supported by V. Grover et al. (2020) who argue that data-driven big data research currently focuses more on the data and techniques, and less on the theory, which results in more locally focused research, rather than higher-level theoretical constructs and abstractions. However, IS researchers should aim to create broad, generalisable knowledge that can be built on by others, and this applies for big data research as well which could be used to better understand the broader issues related to use of technology and information in a social context. Nonetheless, data-driven IS research indicatively lacks a connection with the theoretical building blocks derived from management theory, organisation theory, behavioural theory, computer science theories and systems theory (Kar & Dwivedi, 2020).

Lyytinen et al. (2020) suggested that the emergence of metahuman systems, which join human and machine learning, will inevitably push IS research in new directions that may involve a revision of the research goals, methods, and theorising in the field. Moreover, Duan et al. (2019) proposed that it is necessary to theorise the use of AI and its impact on decision making in order to provide a systematic understanding through an integrated conceptualisation. Since the overall aim of BDA is to enhance decision making by discovering hidden patterns and knowledge, it has become a core element in organisational or strategic decision making nowadays.

Accordingly, big data and analytics must build their own roots in the universally acclaimed decision theory alongside the decision-making process, the decision maker, and the decision, and the resulting relationships and roles of each of these five elements needs to be further studied. Due to a lack of available research incorporating the classical elements of decision making, with the modern additions of big data and analytics in decision theory, the motivation has been found to develop a theory of our own as a basis for future research. Moreover, Arnott and Pervan (2008) highlighted an ongoing concern in IS research that there is a widening gap between research and practice. Thus, the practical relevance of research should be determined by maintaining a close link with the industry and organisations. The following subsection provides some relevant cases suggesting a need for the theory in practice.

5.2. The need for a new theory in practice: algorithmically driven to failure, or success?

In 2018, the Swedish Public Employment Service (PES) deployed an automated decision-making system intended to increase efficiency by automating the process of checking if people receiving a certain type of unemployment benefit keep up their obligations, or else to issue warnings or withhold payments. However, officials had to look into the system after they noticed it was failing to generate letters to expected welfare claimants. Consequently, it was found that between 10% and 15% of the computer's decisions were most probably incorrect, and welfare payments were stopped for up to 70,000 of the unemployed. The news of the failing system came only three weeks after the employment service had announced it was laying off up to 4,500 of its 13,500 employees and cited a budget cut of €75 million between 2018 and 2019. It was further clarified that the Swedish public administration had begun to replace people with algorithms to decide on everything from welfare payments to child support and sickness benefits. Without clear oversight, the failure of such systems affecting so many people is discerning (Wills, 2019).

Near the same time, there was news about the Finnish Tax Administration regarding some mistakes in their automated tax assessment process. Although on a much lower scale of severity, concern was still raised by the ombudsman towards securing legal protection, good administration, explainability, and accountability in automated decisions (AlgorithmWatch, 2019).

On the other hand, also in 2018, New Zealand's Accident Compensation Corporation (ACC) implemented an in-house automated system for processing personal injury claims. The main difference was that the system could not decline claims, and could accordingly only accept straightforward ones. Any incomplete or complex claims were flagged for manual processing by a human. Thus, by limiting the jurisdiction power of the tool and not eliminating the human decision maker from the process, what could have potentially been a high-stake decision has been converted to an extremely low-stake one because the tool cannot decide adversely (Zerilli et al., 2019).

Moreover, the Dutch tax organisation utilised big data and analytics to reduce costs and improve compliance. The big data chain started by collecting data from public and private organisations and combining it with their internal systems, improving the data quality and extensively preparing and preprocessing it for analysis, analysing the data to identify patterns, and finally preparing the results for use by human decision makers. The implementation of the process was tedious, complicated, and required immense research and change, yet it finally managed to work and add value to decision making (Janssen et al., 2017). So although these examples may have also led to letting go of employees and had their own set of arising challenges, the clear failure associated with the PES's case was avoided. But why?

Accordingly, the reasons for such successes and failures in data-driven decision making need to be pinpointed. We can endeavour to explain some of the problems by attributing the failure of the PES to the fact that the human decision maker was eliminated from the loop, and the risk of removing human intelligence was undermined; however, the ACC avoided this by utilising the machine to support, rather than to eliminate, the human decision maker. Nevertheless, neither in scientific research nor in practice can we continue attempting to explain on our own accord, without sound theories or empirical evidence to back these elucidations up. Despite the severe impact of such decisions and their influence on society and the future of millions, classical decision theory on its own cannot explain what happened. This is simply because the previous examples include two elements, the big data and the analytics, which classical decision theory does not clearly define. This inexplicability in itself is a major challenge, since the problem consequently cannot be interpreted, avoided, or resolved.

On another note, Mezias and Starbuck (2009) highlighted the importance of the data element in decision making, and that inaccurate or unreliable data leads to decision failures. They pinpointed the problem that managers and decision makers receive erroneous and distorted information, as well as much more information than they can possibly process. This lack of reliable evidence has led to many problematic decisions, such as those of political invasions and wars, the many strategic ventures of a large telecommunications company, as well as the case of a multinational oil and gas company

(Royal Dutch Shell) when they failed through a series of poor decisions over a decade, costing billions of dollars and control over critical assets.

The significance of the proper usage of analytics and big data in decision making has been reflected in multiple other examples, such as the case of the Danish Primera Air, which was established in 2003 as a low-cost carrier, and eventually fell to its demise in 2018. One of the prominent reasons for its failure was its inability to capture big data, such as social media, flight data, and customer data, as well as utilise BDA to inform their strategic decisions. This led to its operation on wrong routes, increased risks, and financial disaster, as opposed to other airlines, such as American, United Continental, British Airways, and JetBlue who have invested substantial resources into their data-driven decision processes and successfully took advantage of big data and analytics in their decisions (Amankwah-Amoah & Adomako, 2019).

Janssen et al. (2017) discussed many factors influencing data-driven decision-making quality in association with their case study on the Dutch Tax organisation. Among these factors were the big data quality, analytics capabilities, collaboration, flexible infrastructure, process integration and standardisation, and decision-maker quality. Their study showed that an unreserved dependence on the data and analytics led to wrong judgements, complaints, and reckless errors. Depending on the situation and context, the data and analytics need to be carefully selected and utilised to support the experienced decision makers or knowledgeable actors in a standardised process. Hence, they are considered as separate factors. They further argued that it is often assumed that big data and analytics result on better decisions, but this might be a too simplistic assumption associated with a lack of research in the topic. On the other hand, a chain perspective needs to be taken so as to glean a deeper understanding of the diverse set of factors influencing data-driven decision-making quality, and their association and interdependence with other processes and activities.

This chain perspective is evident in Audi's holistic approach in leveraging the benefits and capabilities of big data and analytics in its successful adoption of data-driven decision making, not only in sales, but also in most organisational functions (Dremel et al., 2017). Likewise, Porsche successfully adopted the use of AI to make complicated region-specific production decisions, accommodating for shifts in market demand and regulatory environments, continually adjusting predictions, and improving its ability to allocate the right products to the right market. It was also able to implement an acoustic anomaly system in which AI autonomously learned to recognise potential defects in the production process. By understanding the situations and degrees of collaboration between humans and machines, Porsche was able to make the best of both worlds without eliminating either, and found its own balance between the data-driven decision-making elements (Ransbotham et al., 2020). The previous examples are summarised in Table 1.

Thus, continuing to consider analytics and machines as another type of decision maker defies the definition of a decision maker in classical decision theory, and undermines the importance of the role of human beings. A decision maker is characterised by a bounded rationality, human cognition and perception, inference, emotional behaviour, sense, intuition and judgement, amongst other humanly traits (Hansson, 1994; Simon, 1959). Since machines cannot currently portray such attributes, it should be agreed upon that they are a separate entity, and accordingly require their own element in decision theory.

Table 1. Example cases of data-driven successes and failures.

Case	Factors Contributing to Failure	Factors Contributing to Success	Remarks
Swedish PES (*Wills*, 2019)	• Incorrect decisions generated by the automated decision system. • Replaced human decision makers with machines.	-	• Clear oversight of the automated system is necessary. • Humans should be kept in the loop.
Finnish Tax Administration (*AlgorithmWatch*, 2019)	• Mistakes in the automated tax assessment process (automated decisions).	-	• Securing legal protection, good administration, explainability, and accountability in automated decisions is important.
New Zealand's ACC (*Zerilli et al.*, 2019)	-	• The automated system could only make simple decisions, but could not decline claims. • The human was kept in the loop, while the machine was given limited jurisdiction power.	• Depending on the type, complexity, and stake of the decision, the degree of collaboration between humans and machines can be determined. • Humans should be kept in the loop.
Dutch Tax Organization (*Janssen et al.*, 2017)	-	• Utilised big data and analytics to reduce costs and improve compliance. • Carefully studied and implemented the data-driven decision-making process, combining the value of big data, analytics, and human decision makers.	• Immense research and effort is required to implement a data-driven decision-making process and incorporate the use of big data, analytics, and automated systems, along with humans. • A chain perspective is necessary to understand the factors affecting data-driven decision making and their interdependence.
Royal Dutch Shell, large telecommunications company, and others (*Mezias & Starbuck*, *2009*)	• The lack of reliable and accurate evidence led to many problematic decisions. • Decision makers received erroneous and distorted information, and more information than they could process.	-	• The quality and amount of data affect the decision. • Human decision makers have a limited capacity for processing data on their own.
Primera Air (*Amankwah-Amoah & Adomako*, 2019)	• Inability to capture big data. • Inability to utilise big data analytics to inform their strategic decisions.	-	• The proper usage of analytics and big data is important for informing decisions and keeping up with competition.
American, United Continental, British Airways, and JetBlue (*Amankwah-Amoah & Adomako*, 2019)	-	• Invested into their data-driven decision processes and successfully took advantage of big data and analytics in their decisions.	• Data-driven decision processes require planning and resources. • The proper usage of analytics and big data is important for informing decisions.

(*Continued*)

Table 1. (Continued).

Case	Factors Contributing to Failure	Factors Contributing to Success	Remarks
Audi *(Dremel et al., 2017)*	-	• Followed a holistic approach in leveraging the benefits and capabilities of big data and analytics in its successful adoption of data-driven decision making.	• A chain perspective and holistic view of the data-driven decision process are important for successfully leveraging the benefits of big data and analytics, and understanding the interdependence of factors.
Porsche *(Ransbotham et al., 2020)*	-	• Understood the situations and degrees of collaboration between humans and machines (without eliminating either), and successfully adopted the use of AI. • Integrated the data-driven decision-making elements together.	• A chain perspective and holistic view are necessary. • Depending on the context and situation, the degree of collaboration between humans and machines can be determined, making the most of both worlds.

Table 2. Gregor's (2006) taxonomy of theory types in IS research.

Theory Type	Distinguishing Attributes
I. Analysis	Says what is. The theory does not extend beyond analysis and description. No causal relationships among phenomena are specified and no predictions are made.
II. Explanation	Says what is, how, why, when and where. The theory provides explanations but does not aim to predict with any precision. There are no testable propositions.
III. Prediction	Says what is and what will be. The theory provides predictions and has testable propositions but does not have well-developed justificatory causal explanations.
IV. Explanation and prediction (EP)	Says what is, how, why, when, where and what will be. Provides predictions and has both testable propositions and causal explanations.
V. Design and action	Says how to do something. The theory gives explicit prescriptions (e.g., methods, techniques, principles of form and function) for constructing an artefact.

Moreover, although debated by many renowned scholars, the reference to data in classical decision research has been portrayed a multitude of times in simple, short phrases, such as 'data collection', 'identification', 'information gathering', etc. which were made to sound more straightforward than they actually were (Hansson, 1994; Kalantari, 2010; Mintzberg, 1989; Pomerol & Adam, 2004; Simon, 1959; Tsoukiàs, 2008). Without doing any justice to the importance of data, data has often been overlooked as simply part of the 'intelligence' phase in the decision-making process. While this may have been fine years ago with traditional data and word-of-mouth information, in the era where 'data is the new oil', and big data is a commodity, it deserves its place as an element of its own in data-driven decision theory, and accordingly needs to be carefully studied. Hence, the need arises for a new theory that can support modern data-driven decision-making practices.

6. DECAS as a modern data-driven decision theory

The proposed theory was named DECAS, or the theory encompassing the Decision-making process, dEcision maker, deCision, dAta, and analyticS. DECAS is an incremental qualitative theory which aims to add to the previous concepts of classical decision making. It was developed using Alvesson and Sandberg (2013) proposed methodology for innovative and path-(up)setting research, using 'problematisation' for challenging previous assumptions. Accordingly, in the previous sections, we have identified the relevant literature, as well as the underlying assumptions in the domain, through an extensive literature review (the relevant claims are summarised in Table 2). The assumptions were then evaluated according to the discussed data-driven decision cases, in which we have seen their shortcomings (the critique of the claims is also summarised in Table 2). Consequently, in this section, we developed our own claims, supported through the literature and prior research, and considered them in relation to the audience, in order to build a modern decision theory for data-driven decision making, in particular. Finally, the alternative claims are evaluated in the discussion section.

According to Gregor's (2006) classification of IS theories shown in Table 2, DECAS falls under the 'analysis' type of theory. An 'analysis' theory says what is, but does not extend beyond analysis and description, and does not specify or explain causal relationships or make predictions. Consequently, DECAS aims to state what is within the data-driven decision-making domain, and does not go beyond describing the phenomena of interest and analysing the relationships among the constructs, as well as the scope and boundaries within which the relationships, and observations hold. Hence, no causal relationships or predictions are specified or made.

Moreover, Gregor (2006) defined four main structural components of a theory: (1) a means of representation through which the theory is represented physically in some way, (2) constructs which refer to the phenomena of interest in the theory, (3) statements of relationship among the constructs, and (4) the scope specified by the degree of generality of the statements of relationships and statements of boundaries showing the limits of generalisation. Accordingly, Toulmin's (2003) model of argumentation was chosen as an appropriate means of representation of the components of DECAS in order to structure the theory, and depict the constructs, statements of relationship, and scope through the elements of the model. We have also deemed the model to be suitable for use in phases 4

Table 3. The claims of classical decision theory.

-	Description	Critique
Claim 1	A human *decision maker* follows a *decision-making process* to reach a *decision*, which constitutes the three main pillars of classical decision theory.	The roles of data and analytics have changed. While the intelligence phase in the decision-making process involved gathering traditional structured, or word-of-mouth data, the (big) data characteristic of decisions nowadays is much more complicated. Accordingly, the advanced analytics and automation inherent in modern data-driven decisions, should not be considered in the same way as the simpler analyses of classical decisionmaking, or as substitutes to the human decision maker.
Claim 2	The decision maker is limited by a *'bounded rationality'* which usually leads to *'satisficing decisions'*.	Human decision makers are no longer bounded with the same restrictions as those prevalent in the times of classical decision research. Modern scientific research and technological advancements have allowed humans to reach unforeseen limits and capabilities.
Claim 3	The decision maker considers a set of *acts, events, outcomes*, and *payoffs* to select the best *alternative* in order to reach a *decision.*	This simplified model of decision-making has been critiqued in classical decision theory due to its actual complexity and the cognitive limitations of humans in comprehensively perceiving the environment and processing the necessary information on their own.

Table 4. DECAS claims as portrayed by applying toulmin's model of argumentation.

	Element	Description
Claim 1	Claim	A human *decision maker* follows a *decision-making process* to reach a *decision*, while incorporating *(big) data* and *analytics* as supporting elements, in order to enable modern, data-driven decision making through these five pillars.
	Grounds	In order for organisations to compete better, they need to be able to utilise today's analytics and exponentially growing amounts of big data in their favour, as well as integrate them with the classical elements of decision making. The number of organisations aiming for such data-driven decision making is increasing. Additionally, some political regimes, such as the EU, are enacting directives in order to widen, and sometimes enforce, the use of data-driven decision making in association with certain decision types, like strategic decisions.
	Warrant	Because data-driven decision making helps organisations to enhance their competitiveness, reduce decisions which are made based on gut feelings, become compliant, and leverage the number of quality decisions. These are not viable options without data and analytics being integrated into the decision making of the organisation. Meanwhile, considering the data and analytics simply as parts of the three classical elements, instead of separate elements on their own, is not supported through the definitions of classical decision theory and undermines their importance, thus crippling the potential of data-driven decision making.
	Backing	Since, in data-driven decision making, the decision maker, by going through a decision-making process, utilises the results of analytics on (big) data to find hidden insights, in order to reach or support a decision. Furthermore, applying the correct analytics on a proper selection of data can result in valuable knowledge and insights.
	Qualifier	In cases where data-driven decision making is needed, due to sheer amounts of data, the utilisation of analytics, and the availability of several choices.
	Rebuttal	Unless the decision is not data-driven, and does not require (big) data or analytics. Or, in cases where there is a lack of motivation from the human decision maker to put extra efforts to consult the analytical algorithms.
Claim 2	Claim	Collaboration between the decision maker and the analytics (machine), with the utilisation of (big) data, can result in a *collaborative rationality* which may lead to the *optimising of decisions*.
	Grounds	The input of each of the decision maker, the analytics or machine, and the (big data) is of value on its own, even if bounded or limited. Additionally, the analytics (machine) usually allows the human to off-load, or process larger amounts of data more efficiently and effectively than the cognitive capabilities of the brain may allow. Hence, combining the inputs and outputs of each can lead to a higher level of rationality, and result in an optimised decision (even if not yet 'the' optimal decision) which is likely better than a satisficed one.
	Warrant	Because the goal of decision-making and theory is to reach an optimal decision under the given circumstances, and this might not be feasible by omitting either the knowledge of the human or the insights provided by the analytics.
	Backing	Since, in decision theory, humans are limited by a bounded rationality while machines are also limited in their other abilities than sheer information processing. This prevents either of them from reaching an optimised decision on their own.
	Qualifier	In cases where data-driven decision making is needed, while following a formal decision-making process and assuming: a knowledgeable and informed decision maker, the correct selection of analytics tools and methods, and the correct selection of quality (big) data.
	Rebuttal	Unless prevented by external circumstances or limitations, or either of the qualifiers are clearly not present. Also, in cases where the collaboration is not mutual or is undesired, where too much dependence is put on the output of the machine, or where the analytical algorithms are inflexible and attempt to override human intuition.

(*Continued*)

Table 4. (Continued).

	Element	Description
Claim 3	Claim	By integrating the five pillars of data-driven decision making, the decision maker can be presented with a more comprehensive set of *acts*, a better prediction of external *events* and their effects, a deeper knowledge of *outcomes*, better predictive models of *payoffs*, as well as more evidence and criteria upon which to select the best *alternative* in order to reach a more informed *decision* of higher quality.
	Grounds	The decision maker needs to reach a certain level of knowledge about the acts, events, outcomes, and payoffs in the decision problem domain in order to decide on the optimal alternative. However, due to the decision maker's bounded rationality, this is usually not feasible, and a satisficed decision is achieved. In order to reach a better decision, at least closer to the optimal decision, more information and insights need to be attained.
	Warrant	Because the goal of decision-making and theory is to reach an optimal decision under the given circumstances, and the quality of the decision is affected by the quality of each of the process, the decision maker, and the available information, which might not be enough without (big) data and analytics.
	Backing	Since, in data-driven decision making, the application of analytics on (big) data may result in the extraction of hidden patterns and information otherwise unknown, deeper knowledge and insights, and/or the provision of predictive models and capabilities, which can in turn enhance decision quality.
	Qualifier	In cases where data-driven decision making is needed, while assuming: a knowledgeable and informed decision maker, the correct selection of analytics tools and methods, and the correct selection of quality (big) data.
	Rebuttal	Unless prevented by external circumstances or limitations, either of the pillars are omitted or not correctly utilised, either of the qualifiers are clearly not present, or a proper balance between the pillars is not found.

and 5 of Alvesson and Sandberg (2013) methodology for portraying the alternative assumption ground and considering it in relation to its audience.

Toulmin (2003) introduces six elements to assess the argumentative structure of recommendations, theories, and propositions. The first three elements are essential to any argument, and they are the claim, which is the basic purpose of the argument, the grounds, which are the foundation of the argument or the supporting evidence or facts, and the warrant, which implicitly or explicitly generally supports the grounds and links it to the claim. The other three elements may be added as necessary, and are not essential (Karbach, 1987). Hence, the backing is a statement relied on to back up and establish the reliability and relevance of the warrant, the qualifiers are statements which limit the strength of the arguments or propose conditions under which the warrant is true, and the rebuttal acknowledges exceptions and circumstances which might invalidate the claim or the supporting arguments (Karbach, 1987; Wale-Kolade et al., 2013).

Consequently, the structural components of DECAS are as follows: (1) the theory is represented using Toulmin's model of argumentation, (2) the constructs are identified and italicised in the claims, (3) the grounds, warrants, and backings are used to describe the theory and the statements of relationship between the constructs (since this is an 'analysis' theory, we do not explain the type of relationship, but simply describe that a relation exists between the elements), and finally (4) the qualifier and rebuttal are used to specify the scope of the theory.

Thus, the relevant claims of classical decision theory pertinent to this research, along with their shortcomings relative to current data-driven decision making, are portrayed in Table 3. Subsequently, the corresponding additions proposed by the modern data-driven decision theory are depicted in Table 4. The theory is divided into three claims, and the concepts of the theory are written in italics. A summarised diagram of the theory can be found in Figure A1, in the appendix.

Accordingly, the correct integration of and collaboration between a formal decision-making process, a human decision maker, analytics (machine), and big data are all necessary to reach more informed, quality data-driven decisions than those which would have been made otherwise.

7. Discussion and evaluation of DECAS claims

Earlier in the paper, some examples of data-driven failures and success of decisions were portrayed. Had there been clear theories, methods, and principles in research regarding data-driven decision making at the time, some failures might have been prevented from the start. Hence, the need for a new theory was evident. DECAS addresses this problem, by providing basic arguments for data-driven decision making. In this section, the three claims of DECAS will be discussed in accordance to the previous data-driven decision examples, for evaluation.

7.1. Claim 1 – the (big) data and analytics as additional elements

The first claim incorporates two separate elements, the (big) data and the analytics (machine), with the traditional elements of classical decision theory, which are the decision-making process, the decision maker, and the decision. These elements are supporting, interrelated, and necessary for data-driven decision making, and accordingly neither one can be eliminated, disregarded, or overlooked.

By reflecting on the case of the Swedish PES, it can be argued that the main reason for the failure was removing the human element from the decision-making process and relying solely on the machine. The Swedish government has since done extensive studies and work in developing policies and accelerating automation across industries (AlgorithmWatch, 2019).

By looking at the first argument of the theory, it becomes clear that the human decision maker cannot be removed from the decision-making process, since analytics and algorithms are not substitutes to the human mind, but rather complementary or supportive elements. Accordingly, a balance between the elements must be sought in order to gain the most benefit and reach the best available decision. If this balance could have been found when the PES had started planning the automation of its decisions, it would have realised that there still existed a need for human employees which could not be eliminated, and it could have planned the process accordingly to avoid such a failure. Its aim would have been enhancing the decision rather than completely automating it, and it could have instead gleaned the benefits realised by the ACC and the Dutch tax organisation.

Additionally, with DECAS, the other corporations, governments, and multi-national organisations previously glimpsed upon in Mezias and Starbuck's (Mezias & Starbuck, 2009) work could have known to invest more effort and focus in getting the right, reliable data in order to avoid immense, costly, and terribly consequential failures in their decisions. By understanding beforehand the importance of data as a core element of data-driven decision making, more caution could be exercised to ensure that the right data is analysed correctly. Moreover, Primera Air may have been able to keep up with its competitors instead of filing for bankruptcy had it realised that traditional decision making, without the correct data and analytics, is no longer enough to advance in the data-driven digital era. On the other hand, Audi and Porsche successfully led by incorporating each of the elements and finding their own integration and balance.

Nevertheless, it is important to note that our theory does not imply that having the five elements leads to success, or vice versa, as there are many other contributing and external factors to the outcomes of decisions. However, the five elements are crucial pillars to data-driven decision making, and the role of each should be studied separately, along with their interrelation as a whole. Accordingly, an appropriate level of integration and interaction, should be sought between them, which thus requires further research.

7.2. Claim 2 – a collaborative rationality for optimising decisions

Which brings us to the second argument, where it is claimed that collaboration between the human and the machine can lead to a 'collaborative rationality' which is not bounded by the limitations of either one on their own, and can ultimately lead to the 'optimising' instead of 'satisficing' of decisions. The concept of collaborative rationality is adapted from Innes and Booher's (Innes & Booher, 2018) definition, which is grounded in Habermas' (Habermas, 1984) notion of communicative rationality. Accordingly, it is extended to describe a process where the involved parties, including humans and machines, jointly participate in bringing their various capabilities to solve problems together. All participants must be informed, and able to express their views. Techniques must be used to assure the legitimacy, comprehensibility, sincerity, explainability, and accuracy of what they convey, and nothing should be hidden. This further requires that all involved parties understand the tasks, responsibilities, and obligations, and high level of transparency is provided (Trunk et al., 2020). Such a collaboration, if properly researched, may bring us closer to the optimised decision so inherently discussed in classical decision theory, yet so far unattainable due satisficing and the limitations of individual rationalities.

So either by integrating the knowledge and experience of employees within the automated decision-making process (note that despite the possibility of automated knowledge integration, the human still needs to supervise the process), or by using the analytics and algorithms to automate pattern extraction and provide hidden insights to the human decision maker, who accordingly makes the final decision, this collaborative rationality is necessary when aiming for optimal, or near-optimal, decisions. So had this theory been available to the PES beforehand, they could have realised that the optimising of decisions is not synonymous to automation. Contrarily, both the human and the machine elements should have coexisted and collaborated to reach a higher level of rationality, unattainable by any single element individually. While the human may be bounded by certain cognitive and computational limitations, the machine is no less bounded by its own set of problems. Although algorithms may be faster and more efficient in countless cases, they simply do not benefit from the perplexing, complex structure known as the human brain. Human judgement, perception, intuition, emotions, understanding, common sense, along with many other features, cannot be interpreted or displayed by a machine with 'artificial' intelligence. Hence, we cannot expect that the delegation of decisions to automated machines is without risks and consequences, or altogether an utter failure, as was seen in the successes and failures of the previous cases.

Additionally, several implications for automated decisions have been shed light upon by the General Data Protection Regulation (GDPR) and its interpretations, which prohibit some forms of fully automated decision making without meaningful human intervention. Accordingly, human-centred automation is a way to ensure that human is kept in front and centre in the decision and control loop (Wagner, 2019).

Furthermore, Duan et al. (2019) argued that AI can play multiple roles in decision making, of which it will mostly be accepted as a decision support tool, rather than to replace humans, and that its effectiveness differs depending on the level of the decision. Moreover, Bader and Kaiser (2019) highlighted that the boundaries between human and algorithmic intelligence blurs when users are confronted with opaque algorithmic decisions. This leads to a debate over which should have control over decision making and have power over the other; because when their roles become unbalanced, negative consequential effects arise.

While the potential for combining AI and human intelligence to maximise the value of collaborative intelligence is significant, it requires many considerations. AI is a key enabler for making intangible assets accessible by capturing, organising, and sharing information for enhancing decision making. AI systems can also analyse big data, often in real-time, and transform data pieces into useful information. However, human intelligence is critical in deriving the implications of the AI analysis, accordingly translating information into knowledge, answering 'so what' questions, and deciding on an appropriate course of action (Paschen et al., 2020).

Lyytinen et al. (2020) also raised the importance of researching metahuman systems, or sociotechnical systems where machines that learn to join human learning, thus complementing and amplifying their capabilities. They further identified an IS research agenda with four organisational level functions for properly organising such systems: delegation, monitoring, cultivating, and reflecting. Gupta et al. (2018) also highlighted the importance of future research on cognitive computing, with the goal of building a rational, combined, and collective mechanism motivated by the capability of the human mind and strengths of AI systems. Furthermore, Trunk et al. (2020) shed light on the current state of research on combining human and machine intelligence for strategic organisational decision making and provided a conceptual framework for AI integration into organisational decision-making processes. Accordingly, there is a synergy between the unique strengths of humans and machines, augmenting the intelligence of one another; however, the level of collaboration differs according to the tasks and types of decisions on hand, which still requires future work.

In a similar note, Ransbotham et al. (2020) identified five main modes for humans and machines to interact, depending on the decision context and type. Either the machine decides and implements, with humans supervising and maintaining compliance, or the machine decides and humans implement the solutions, or the machine recommends, and the human makes the decision, or the machine generates insights, which inform humans in the decision process, or finally the human generates the choices and hypothetical situations, and the machine evaluates them. They further suggested utilising more than one mode in order to reap more benefits. However, choosing and implementing the most appropriate and beneficial mode of interaction is not so simple. This brings us back to the importance of studying the concept of integration between the elements and its implications, as well as the degree of collaboration between humans and machines.

7.3. Claim 3 – integrating the five pillars for more informed decisions

Finally, the last argument of the theory suggests that by integrating the five pillars of data-driven decision making, the correct selection of analytics methods and techniques on the proper set of data can result in providing the informed and knowledgeable decision maker with: a more comprehensive set of acts which can be done, a better prediction of external events and the consequences of their effects, a deeper knowledge of outcomes due to extraction of hidden insights within the data, better predictive models of payoffs, and consequently more evidence and criteria upon which to select the best alternative in order to reach a better, and more informed decision than that which would have been made without any of the five elements.

We have already discussed that the PES removed the essential element of the human decision maker from the process, and hence failed at reaching quality decisions. However, had they, along with the previous examples and countless other organisations and entities, understood the grounds of this claim, they would have realised that the role of data and analytics is rather to provide more information, insights, knowledge, and patterns to the human decision maker throughout each step of the clearly defined decision-making process. This subsequently leads to a better view of the acts, events, outcomes, and payoffs of traditional decision making by taking into account more collective factors and information than could have been perceived by an individual, and ultimately supporting the decision maker in reaching more informed, optimised, quality decisions. Hence, we can see that applying this theory might have helped all of these organisations, governments, and corporations prevent their decision failures from the start instead of having to face the consequences after they had occurred.

Moreover, by applying DECAS to New Zealand's ACC example, it is seen that they evaded failure by keeping the human in the loop, and not relying on the machine. The decision-making power of the machine was limited, based on the data of the claim, and only served as support rather than replacement for the human element. Additionally, the decision-making process was clearly defined and continued to be followed, even by the algorithm, with minimal alterations. So, although this case may not portray the full potential which can be reached by correctly implementing data-driven decision making, it supports our theory that the five elements must be present together and a balance needs to be found between them.

Additionally, our theory supports the claims in research highlighting the importance of data in decision making, the need for a balanced, data-driven culture in organisations, and the importance of studying the integration of big data and analytics with organisational decision making in order to enhance decision quality (Bean & Davenport, 2019; Frisk & Bannister, 2017; Janssen et al., 2017; Mezias & Starbuck, 2009). Accordingly, identifying the (big) data and the analytics/machine as separate elements in data-driven decision theory, requiring their own focus in research and special considerations, is the first step (of many) towards an empirically supported data-driven decision process. However, more research is also required to establish the unique advantages obtained by the combination of big data and AI in decision making, and to measure their impact on decision making from different perspectives (Duan et al., 2019). Hence, it is suggested that further research on the evaluation of data-driven decisions should be partaken.

8. Conclusion

Throughout the paper, we have seen the importance of data-driven decision making, and the need for considerable research in the field for it to mature, and in order to realise its benefits and overcome the associated challenges and implications. While research has aimed to tackle and explain individual, or a small combination of, elements and their problems and challenges, there was an evident lack in coherent theories that could support the data-driven decision making elements as a whole, thus considering it as a phenomenon distinct from traditional decision making.

In this paper, we aimed to partake in such research by developing a modern theory, DECAS, which builds on the classical elements of decision theory, and integrates the data and analytics elements typical of today's data-driven decision-making environments. Furthermore, the need for such a theory, the theory itself and the argumentation behind it, as well the application of the theory were all elaborated. Accordingly, the first proposed claim is that the pillars of data-driven decision making are not only the decision-making process, the decision maker, and the decision, but also the (big) data and analytics as additional elements, to which a balance between the five elements should be sought. The second claim proposes the concept of collaborative rationality, as opposed to classical decision theory's bounded rationality, which through the proper collaboration between humans and machines can bring us closer to the optimising of decisions, rather than satisficing. Finally, the third claim proposes that the proper integration of the five elements, and the correct selection of data and analytics, can lead to more informed, and possibly better, decisions.

The impact of this research on science, is the presentation of a new modern-day theory which can support the elements of data-driven decision making, as it was shown that classical theories are not sufficient for doing so. This theory can serve as a basis for new research and developments in the field, especially in the areas of human and machine collaboration, BDA and metahuman systems.

Furthermore, this research benefits society and organisations by highlighting the elements required for data-driven decision making, and how they can lead to more informed, quality decisions which could have otherwise been unattainable. It can be of value to managers, decision makers, and executives who make data-driven decisions, as well as data scientists, analysts and developers who utilise data, analytics and machine learning for decision making.

Consequentially, this is a utopian view of what can be attained by integrating the five elements of modern data-driven decision making. However, this requires a great deal of effort in order to find a meaningful integration between the elements. The degree of collaboration between the human and the machine, the correct selection of quality (big) data, the appropriate use of analytics methods and tools, the proper selection and definition of the decision-making process, the evaluation of data-driven decisions, and how to integrate all of these elements together, are imperative aspects to study, and we aim to address some of them in future research to further support our claims. Additionally, the conditions that lead to the acceptance or rejection of data-driven decisions need to be investigated (Burton et al., 2020).

Furthermore, the importance of topics such as accountability and traceability, transparency, reliability, evaluation, risk, governance and explainability of the results and the decisions, which have always been questioned in any type of decision, are of increasing relevance in data-driven decision making and must be considered. We find that several of these topics relate to the collaboration between the human decision maker and the machine. With the ubiquitous adoption of assistive AI systems for supporting human decision making, the lack of trust into AI's predictions needs to be addressed. This requires research rendering AI decisions more transparent by providing explanations, and to what extent these explanations help in fostering trust (Schmidt et al., 2020). Moreover, with the emergence of metahuman systems, there is a new shift in research towards human/machine learning systems and they major differences they exhibit (Lyytinen et al., 2020). Accordingly, our future research will further study the concept of 'collaborative rationality'. Since the future of decision making is based upon this collaboration, then it must be carefully researched, and many questions need to be asked.

Future research needs to address the following questions: does the collaboration depend on the type of problem? Is the relationship between the human and the decision constricted to certain types of decisions, such as long term or strategic, tactical, operational, unstructured, semi-structured, etc.? How can the decision be explained; since algorithms are known for their black-box nature, how can this be overcome? Who is accountable for decision errors in this case? Errors in decision making used to be generated separately by humans and machines, now with such a combination what kind of new errors and challenges arise? How can human decision makers be trained in data and analytics, with specially focus on basic statistical concepts such as accuracy, errors, and uncertainty? Lastly, how to design data-driven decision making so as to keep the human-in-the-loop and allow human to semi-supervise the decision-making process, rather than being supervised by the algorithms? Therefore, all these implications need to be extensively explored before data-driven decision making can reach its full potential.

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Appendix

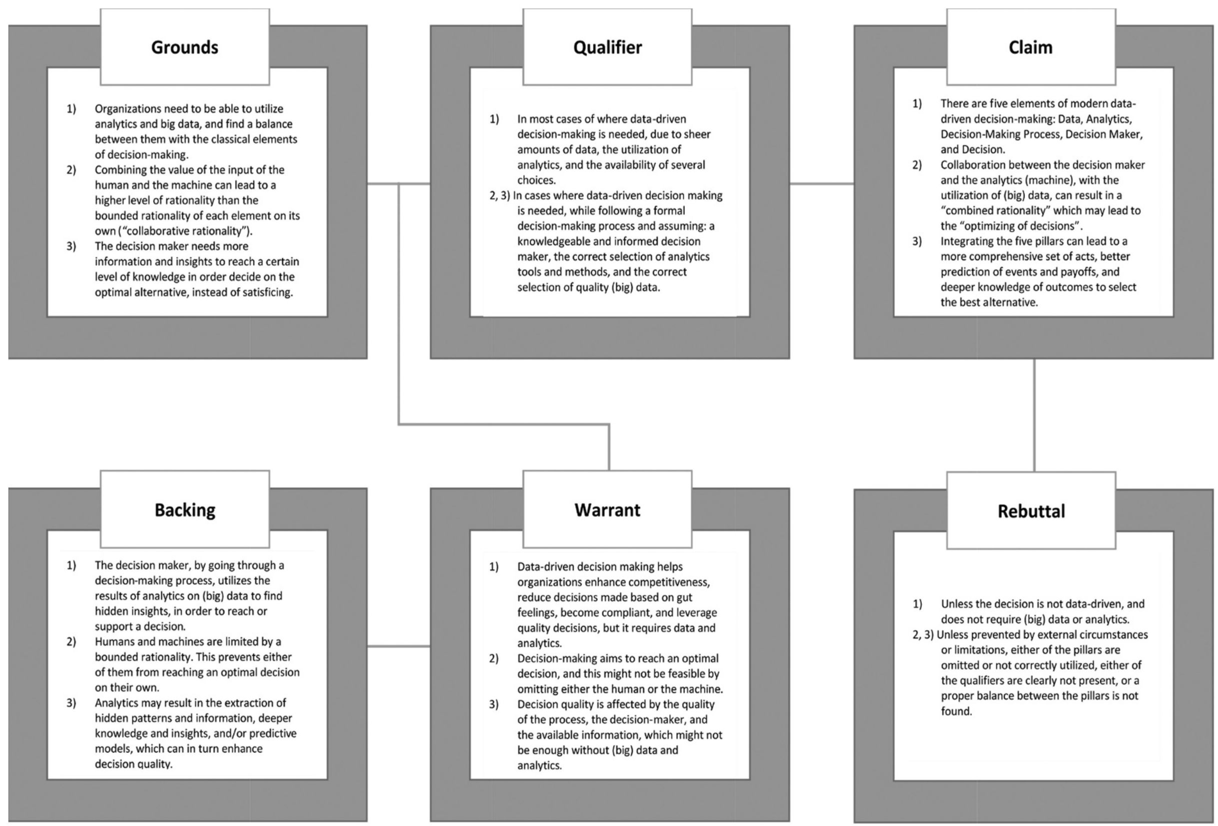

Figure A1. A summarised diagram of DECAS's arguments.