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Wise Data-Driven Decision-Making

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Abstract. This article reports on the preliminary findings of research in progress. In one of the first empirical studies in the information systems and organisations literature, we investigate the role of wisdom as a decision-making capacity in the use of analytics. To address the research question of how decision-makers can use analytics to make wise decisions, we interviewed six decision-makers and four data analytics in a diverse range of industries. Based on the findings, we introduce a process model of wise data-driven decision-making (WD3M). This study offers significant theoretical and practical implications as it extends our understanding of how wisdom can be defined and used in the analytics context. For practitioners, this study offers important guidelines as to how to make wise and more effective data-driven decisions.

Keywords: Business analytics, Wisdom, Knowledge, Decision-making, Data analysis.

1 Introduction

For many organisations, business analytics is the new frontier in the information revolution [1]. They have gained significant attention from academia and industry [2] as a disruptor to organisations [3]. Essential stories hidden in big data are powerful means to enhance the interpretation of environmental scenarios by decision-makers [4]. Business analytics, or simply analytics, aims to create economic and social values [5] for organisations using big data [6]. It offers different ways to support users efficiently with information on decision-making scenarios [7], where technology, human perception, and organisations as interpretive systems combine to assist decision-makers in improving their information processing capabilities and enhance the understanding of the business environment [8].

Despite analytics being one of the essential elements of the modern decision-support system [7], in most organisations, analytics is loosely coupled with decision-making and much less with wise decision-making [9]. Many researchers observe that its use for decisions involves several issues [2] for dealing with fuzzy and ambiguous situations [10]. Decision-makers also work in groups, and social aspects are indispensable in making informed decisions [11], especially when encountering non-linear and complex decision situations [12]. Indeed, what decision-makers need from new analytics tools is capabilities that enhance their understanding, non-rational decision-making and satisficing, and knowledge implementation capacity.

The current literature on socio-technical features of analytics is characterised by a limited number of empirical studies [5] and calls for interdisciplinary research drawing on theories from psychology and sociology. The success of analytics in organisations requires not only infrastructure, data analysts, and knowledge and tools for dealing with big data but also an understanding of how analytics should be used wisely to translate big data to competitive advantages and wise decisions [13]. It is, therefore, crucial to investigate “how can decision-makers use analytics to make wise decisions”?

To address the research question, this study draws on the notion of wisdom. Wisdom is the process through which the problem is defined, the right alternatives are formulated, the most appropriate alternative is selected and implemented using the right means towards achieving the right end at the right time [9]. Wise decisions find impression in socially complex and ill-defined problems. These problems are characterised as emergent, dynamic, unpredictable, and difficult to formulate, encompassing numerous multi-directional cause-effects relationships, and engaging multiple stakeholders both within and outside the organisation. Most organisational strategic decisions are of this kind [9]. By employing the wisdom model, this study pursues the following objectives: (i) to conceptualise wisdom in the context of analytics; and (ii) develop a process model to show how organisations can make wise decisions based on analytics.

The following sections first present the theoretical framing of the study, followed by details of the research method and its design, and a description of the data collection process. Then it presents the analysis of the collected data along with the proposed process model of this study. Finally, the paper concludes and elaborates on how we will continue data collection and its analysis to complete this research.

2 Background

Making effective decisions based on both rational (e.g., using analytics) and non-rational (e.g., human insight and judgment) is at the heart of the notion of wisdom [9]. The notion of wisdom describes the evaluation of multiple perspectives to better understand the causes and ramifications of problems, which is an essential prerequisite to reaching effective decisions positively. Wisdom is the capacity to understand the relationship among and give meaning to objects, events, and human interactions by critically reflecting on the past (causes), present (manifestation), and future (ramifications) of the phenomena and their relationships. The notions of wisdom is based on right ‘mean’, ‘time’ and ‘end’. The ‘right mean’ means that the selected alternative or solution should not involve the use of any coercion. The ‘right time’ refers to the decision to be made when it generates the most positive impact. The ‘right end’ means that the decision is made based on considering the legitimate and ethical interests of stakeholders.

Wisdom has been the topic of philosophical discourses for centuries. The concept is rooted in the works of philosophers such as Socrates and Aristotle. Interest in wisdom has revived over the past three decades. Contemporary studies of wisdom began by psychologists and gerontologists. More recently, other disciplines, including organisa-

tion and management studies [14], leadership [15], public administration [16], and education [17] examined the implication of wisdom. The information systems and the knowledge management scholars have joined the discourse. For example, [18] revisits the data–information–knowledge–wisdom hierarchy as the widely accepted model in the information systems and knowledge management disciplines and emphasises that the model is more about wisdom, as the ability to increase effectiveness than knowledge. [19] Discusses the individual, organisational, and societal issues related to contemporary technologies and argue that the use of technology requires a critical review based on the wisdom theory to enhance human well-being.

By integrating both rational and non-rational aspects of decision-making, wisdom can address the challenges of using organisational information systems to make insightful decisions based on analytics. In this sense, we argue that wisdom as a decision-making capacity can sit between analytics and decisions. [9] proposes a model of wisdom that conceptualises wisdom as a decision-making capacity to identify and solve complex problems based on (1) an understanding of both the internal and external world, (2) both rational and non-rational analyses of the problem at hand, and (3) a consideration of multiple stakeholders' perspectives.

We adopted the wisdom model as a theoretical framework in this study because wisdom is a more comprehensive concept in meaning than making decisions. Decision-making focuses on evaluating a range of possible actions and selecting the best alternative to the extent that the problem is solved [20]. While the attention of decision-making is directed almost entirely to solving the problem at hand and the future direct impact of decisions, actions, and their outcomes, wisdom necessarily deals with both the short- and long-term direct and indirect impacts of any possible solution on multiple stakeholders and from both the organisational and ethical perspectives.

From an analytics perspective, a decision-maker can make quality decisions after a lengthy and thorough process of information processing, especially at the strategic level. Little is, however, known about the process through which a decision-maker, especially strategic managers, can make wise decisions based on analytics.

3 Method

We have conducted pilot interviews with study participants from separate organisations to identify their personal experience in using analytics in making wise decisions. In the rest of this research, we will also use other data sources such as documents or log data. We will continue data collection until we achieve the theoretical saturation on the aspects of participants' experiences that are the focus of this study. We have interviewed four data analysts who work with advanced analytical tools and six managers and directors who use the garnered reports by data analysts to this stage of research. In the rest of this study, we use pseudonyms to refer to the study participants.

As the focus of the study is on organisational decision-making, we have chosen the study participants mainly from large enterprises. We have used semi-structured questionnaires during the interviews as a guide to the free-flowing discussion [21], and we have asked study participants to provide examples of business situations where they

observed either wise or unwise data-based decisions. We followed a cyclical and recursive process of data collection and prepared transcripts, and analysed them gradually. Going through the interview transcripts, we discovered the concepts related to the use of analytics in organisations, and then we used thematic analysis to identify the fundamental themes of this study, using Strauss and Corbin's guidelines [22]. These themes include the concepts associated with using business analytics within organisations for wise decision-making. In the following section, we elaborate on the preliminary data analysis by elaborating on the four identified themes.

4 Preliminary data Analysis

This section elaborates on four discovered themes that elaborate on the wise use of analytics in organisations. We have taken the organisational context of analytics into account to draw a more socio-technical characterisation of themes. The cyclical process of data collection has helped in preparing transcripts and analysing them. Concepts related to the use of analytics in organisations were dubbed with preliminary codes by reading the interview transcripts. These codes include the concepts associated with using analytics within organisations for wise decision-making. The four identified themes are 1) report generation, 2) trustworthiness analysis, 3) appropriateness analysis, and 4) alternative selection.

4.1 Report generation

An effective decision is based on an accurate understanding and articulation of the problem. If the decision-makers fail to identify and formulate business problems accurately, they can't use data and information to articulate possible solutions. Our study participant, Dominic, Director of an IT firm, added to this view by noting that the main issue for understanding an organisation and its surrounding environment through analytics is clarifying requests of decision-makers rather than analytical functionalities.

The analytical skills of decision-makers influence their interactions with reports and affect analytics use in understanding organisational complexities. Christopher, Director of a government firm, identified the lack of proper interaction between data analysts and decision-makers as the primary barrier to unskilled decision-makers using analytics. Rebecca, Director of a government firm, further added to this view by highlighting the role of communication for data analysts and the extent to which proper presentation of their work could assist decision-makers to understand underlying concepts and influence the efficacy of analytics. She then captured the essence of analysts facing decision-makers who could not understand the reports presented to them, as she talked about failing to explain her work despite the robust model she had developed. In this sense, the wise use of data for better decision-making requires the decision-maker to understand the data clearly. Both analysts and the decision-maker should be consistent in terms of the data analysis results concerning the decision problem at a given time.

4.2 Trustworthiness analysis

In the view of our study participants, sceptical decision-makers feel they lose their power if they make decisions based on analytics or they do not trust the validity of analytics reports. Wise decision-makers may also be sceptical in that they do not easily trust in data. Wise decision-makers also check the validity of data before they use it. In this sense, they are sceptical. On the other hand, they rely on data when they feel that the data is trustworthy and can lead to effective decisions. That is, the wise decision-maker will rely on data, even if they may be seen as incapable of making decisions solely based on their knowledge and experience.

Matteo, Director of a finance firm, noted that a lack of trust is even more problematic when reports recommend a solution to decision-makers. Austin, Manager in a healthcare firm, indicated that analytics could usually provide a straightforward comparison between objectives and progress; however, for reports at the strategic level, more effort is required to analyse the suitability of the analysis and solutions for the problem in hand. Rebecca further elaborated on sceptical decision-makers resistance in established organisations and suggested presenting analytics in a plausible and easy-to-understand way for decision-makers. Providing decision-makers with the opportunity to interact with and validate reports assists in analysing the trustworthiness of analytics. Wise decision-makers will not make decisions based on the data if they do not trust it. Joseph, a National manager in a government firm, also suggested interactive reports as a solution to improve the trust of decision-makers toward analytics since they lose confidence in using prescribed solutions and prefer to control and investigate what is behind reports. He further suggested engaging with decision-makers and personalising reports, and noted that decision-makers need assistance and training to interact with reports. He also explained that decision-makers would feel they have control over what they are using, leveraging their confidence in using analytics for decision-making after this interaction and engagement. Trust in data is, therefore, a critical aspect of wise data-driven decision-making.

4.3 Appropriateness analysis

Wise decision-makers usually have ideas about appropriate solutions; they check the data to see if the data back up those right decisions. In this line, Chadrick explained that intuitive decision-makers are looking for specific numbers or patterns that they already have in mind, and analytics provides them with numbers to support what they consider possible solutions. Rebecca noted that intuitive decision-makers use analytics to justify their actions. If there is any inconsistency between the data and the possible wise solutions that the decision-maker has in mind, wise decision-makers seek more data. For example, data should show a potential market for a particular product or service in the country. A wise decision-maker would not go ahead and supply that particular product or service if the product or service may have negative side effects on the potential customers; or if there is a cultural or religious sensitivity to that particular product and service.

Our study participants noted that, in these situations, extensive reports are not useful, and data analysts should focus on the lower level and operational drivers. Rebecca

added that analytics should be used as a validation tool rather than an absolute prescriptive solution. On the other hand, and as discussed in the trustworthiness analysis, wise decision-makers do not ignore data when they see that the data can lead to a more effective decision.

4.4 Alternative selection

Decision-making is about facing many situations of choosing alternatives. Wise decision-makers know that they need to use reports at the right time and have to respond to the real world rapidly. However, the analytics and IT-related processes may play against making timely decisions. Usually, in organisations, IT teams and analytics teams have their standards and processes, and many other business stakeholders also need to review their work. Ryder, a senior business analyst in a finance firm, mentioned that the process of preparing reports and using them is very lengthy, and decision-makers should wait for various pieces of data that some data suppliers can provide. Also, the processing time is required for technology and data analysts to bring this data and analyse it.

Shaden, a manager in a government firm, emphasised using KPIs to quantify strategic decisions and turn them into everyday operational actions. Wise decision-makers drill deeper into existing reports or create new stories to better understand business operations. Diego, a data analyst in a finance firm, also highlighted the role of interactive reports in gaining insight and choosing the alternatives wisely; he noted that decision-makers need to interact with reports and drill them down for additional insights to know their drivers of business functions.

5 Wise Data-Driven Decision-Making (WD3M)

We propose a process model for Wise Data-Driven Decision-Making (WD3M) (see Figure 1). This model incorporates the notion of wisdom into data-driven decision-making to make wise use of data. The wisdom principals are enablers in the model, whereas the data-driven actions (four identified themes from the preliminary analysis) are episodes [23]. We elaborate on the main elements of the process model in the following.

WD3M starts with report generation, which is done by data analysts and monitored and improved by decision-makers. Identifying and considering essential signals from the internal and external environment to unfolding business events buried in masses of business data is a critical pillar in WD3M. The type of discovered insights from the available data depends on the variety and granularity of various data sources [24].

After the reports are generated, wise decision-makers assess the validity of the reports in an episode for trustworthiness analysis. There are two enablers from cognition and emotions of decision-makers when they analyse the trustworthiness of reports.

When decision-makers gained a confidant in using the reports after successfully analysing their trustworthiness, they move to appropriateness analysis. In this episode, in

addition to cognition and emotions, wise decision-makers use their understanding of the internal and external world.

External world understanding means that the decision-makers analyse and interpret the data to understand the environmental context. They check the reports to see to what extent the report represents the external world when needed and to what extent the data represents the reality of the external world or what is happening outside the organisation.

Appropriateness analysis is the central aspect of wisdom. An analytical report and its source(s) can be trustworthy, as is checked in the trustworthiness analysis episode, and perfectly lead to a true understanding of both the internal and external worlds, yet to be inappropriate, as is checked in the appropriateness analysis episode. For example, the data can show that there is a great market for selling adult products or even guns to a community that has a financial justification. However, applying a multi-perspective consideration may identify the solution as an inappropriate solution. By inappropriate, we mean that the decision and its consequences can be unethical, illegal, and ignoring the community's interests. Multi-perspective consideration is an appropriateness analysis of the data, based on three perspectives: ethical, legal, and multiple stakeholders' interests [19].

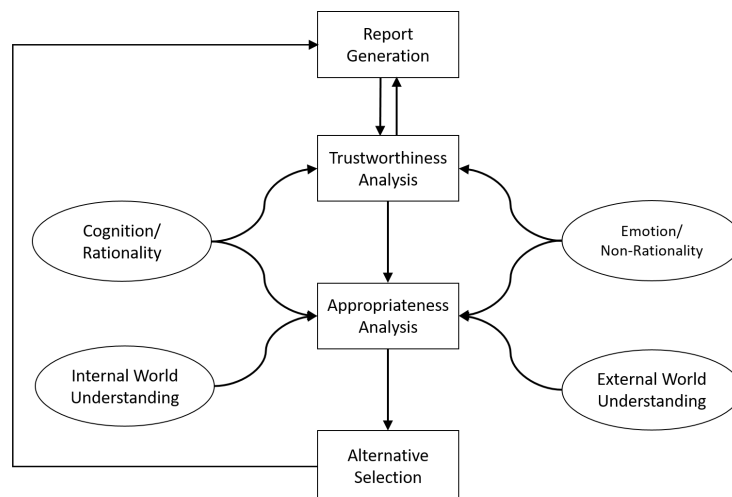


Fig. 1. Wise Data-Driven Decision-Making (WD3M)

Sceptical analysis and cognitive-emotional mastery are also crucial in the success of WD3M. For example, one external agent may provide an analytics report to an organisation about selling the company shares to another company. The data sources are trustworthy from a cognitive or rational point of view. However, whether or not the external agent has intentionally intended to mislead the organisation cannot be necessarily determined by looking at the trustworthiness of the data via an analytical (rational) point of view. The decision-maker may need to rely on his or her non-rational understanding

of why the external agent is providing the data report. Through emotional or non-rational analysis, the decision-maker can, for example, assess the intention behind the data.

6 Discussion

Data analysts can employ an inductive approach to discover previously unknown patterns or distinctions [25] to emerge from big data. Engaging in this approach, data analysts can start from data and then seek to generate theoretical explanations from (wise) decision-makers [5]. Most decision-makers work with data analysts without a defined purpose, promoting a bottom-up, inductive approach to the use of analysis for decision-making [26]. However, what wise decision-making using analytics needs is incorporating both cognition/rationality and emotion/non-rationality from decision-makers.

From cognition/rationality to WD3M: The proposed process model highlights the importance of interactive reports and their insights to assist decision-makers in using their cognition and rational thinking in using analytics. In new analytics systems, data analysts do not need to do a lot of analytics on behalf of decision-makers; they create an environment where end-users apply analytics, except for advanced concepts or some areas where decision-makers might not carry the required skills. Data analysts can be innovative to arrive at ideas and insights; however, specific boundaries can simultaneously be set around their analytics to ensure that business value is delivered [27]. While decision-makers have a list of prepared reports in a typical analytics system, with interactive analytics, decision-makers can drag data onto their workspace, make their analysis, and modify and personalise reports. They can change dimensions or actual financial measures or add calculations on reports. They can start with developed reports, which they can modify and customise based on their understanding.

From emotion/non-rationality to WD3M: The proposed process model suggests a deductive approach in using reports and explains how decision-makers should use interactive reports. Analytics would not be effective unless reports are designed in ways that explicitly include decision-makers in the loop [28]. The integration of rational and non-rational analysis of the appropriateness of the possible solutions requires a high level of interaction between the data analysts and the decision-maker.

Analytics is widely used in automated algorithms for decision-making. However, the literature on analytics also highlights the importance of human intelligence [29] and the wisdom required to examine patterns and insights [30] and to refine them [31]. Along with building on algorithmic decision-making, analytics' stakeholders need to develop strategies to gain insights from big data beyond stable metrics, as the insights gained from analytics largely depend on the exploration of decision-makers.

Decision-makers trust analytics when they interact with reports and validate them. They may also feel they have more power, as they can make sense of and effectively integrate insights into their decision-making [25]. This trust and power can potentially result in more data-driven actions and assist organisations in leveraging the potential of analytics [32]. The study participants who closely worked with decision-makers highlighted

their willingness to anticipate decision-maker's needs and provide them with opportunities to customise and tailor reports. Also, some scholars contend that too much reliance on algorithmic decision-making may lead to a loss of confidence in using relevant knowledge by decision-makers, particularly when decision-makers don't clearly know how algorithms arrive at certain results, patterns, and decisions [33].

Algorithmic decision-making nevertheless has strengths and applications in many cases, and organisations need to devise ways to meaningfully balance this in interactive reports [29], [34]. To this end, scholars have started to explore the interaction between algorithmic and human intelligence and how this leads to valuable insights. In fact, data should be wisely supplemented with decision-makers experiences, common sense, and contextual knowledge [25], to solve problems for which the conditions are unknown. In situations where algorithms are deployed to operate without human intervention, they actively enact the analytics environment, which gives algorithms an increasingly performative character [35], [36].

7 Conclusion

This study took the organisational context of analytics into account, thereby answering a call for a more socio-technical characterisation of big data to investigate how analytics can be used to make wise decisions. To this end, we conducted interviews to examine the strengths and limitations of analytics in the process of WD3M. Drawing on thematic analysis, this study developed a process model that shows how managers can use analytics to make wise decisions.

The proposed model demonstrated how four themes identified in the data – report generation, trustworthiness analysis, appropriateness analysis, and alternative selection, provide grounding for WD3M process. It showed both inductive and deductive approaches for using analytics in various steps for the process of wise decision-making and how these complement each other in this process. It also demonstrated how communication between wise decision-makers and data analysts results in balancing these two approaches. In fact, bridging analytics and wisdom is vital to helping decision-makers understand that analytics has more profound implications for business than just reporting on status. Analytical technology offers ample support for wise decision-making, thus providing management with methods and tools to continuously generate business insights leading to quality and actionable decisions.

This study provided strong evidence for the impact of the research in progress on the theory and practice of wisdom and its technological support. From a theoretical perspective, the study brings together two distinct fields – wisdom and analytics – and demonstrated how the approaches advocated by these two fields could improve the applications of analytics. The explanation of wisdom construct in the context of analytics revealed the strengths and limitations of analytics for addressing wise decision-making. From a practical point of view, this study demonstrated how decision-makers use analytics to improve their understanding of the business environment and make wise decisions. It also provides guidelines for developers to enhance their analytics tools to enable the end-users to make wise decisions.

Methodologically, the findings can potentially be undermined by a multitude of inter-related factors that influence analytics productivity, not all of which were identified in the conducted interviews. As the domain knowledge and experience of decision-makers may affect their interaction with analytics, more interviews with different decision-makers in each could be conducted to investigate how analytics improves wise decision-making. Further studies could also investigate under what particular conditions decision-makers can generate insights through analytics.

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