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The Impact of Real-Time Business Intelligence and Advanced Analytics on the Behaviour of Business Decision Makers

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***Abstract*—Although, there are many tools to support leaders, organizational decision-making processes are still susceptible to errors and biases. Business analytics (BA) is one of the approaches to support managers in making well-informed/evidence-based business decisions. Despite huge investments, BA projects continue to fail. From one side research papers show that managers require information in their decision making process, whereas from another side there are studies presenting that business decisions are often made based on gut feelings and intuitions ignoring part or all of the available data/information. Using experiments authors of this research investigate whether information delivery in the time when the business decision is being made influences or changes the decision maker's mind, and thereby, leads to a different decision outcome. The research contributes to descriptive and prescriptive decision theory and adds to existing literature in the field of BA. The research also, provides insights into selective perception and decision maker's behavior when warnings about decision consequences are given. Based on the obtained research results, this study presents recommendations on how BA solutions can potentially be improved.**

Keywords-business intelligence; advanced analytics; decision making

I. INTRODUCTION

Business intelligence and analytics (BI&A) is one of the fastest growing industries - the market is forecast to reach $18.3 billion in 2017, an increase of 7.3 percent from 2016. By the end of 2020, the market is forecast to grow to $22.8 billion [1]. Over the last decade the role of BI&A has been significantly increased and according to Gartner's CIO survey BI&A will be the most important technology area to help businesses differentiate from their competitors in 2018 [2]. According to the survey of 154 global executives, conducted by the Economist Intelligence Unit, good data is the most important input to decision-making [3]. Despite huge investments, a survey conducted by Paradigm4 in 2014 highlights that 49% of respondents are struggling to manage and process their data in their existing relational databases [4]. Gartner predicts that, through 2017, 60 percent of big data projects will fail to go beyond piloting and experimentation, and will be abandoned [5].

Several research groups have analyzed reasons of BI&A project failures and results show common patterns. Forrester Consulting research of Traditional BI performed in 2014 indicates that 60% of professionals have time concerns with creating and updating dashboards [6]. According to Oracle's survey in 2012 "Big Data, Bigger Opportunities: Plans and Preparedness for the Data Deluge" 45 percent of respondents struggle to report information to business managers as fast as they need it [7]. According to Columbia Business School's research 39 percent of marketers say that their data is collected "too infrequently or not real-time enough" [8]. From these researches, we can infer that required information delivery in the time when it is needed is one of the most important and, at the same time, also one of the most challenging tasks in BI&A that very often fails. Investments in real-time BI&A solutions could help to avoid these problems, but would it have any impact on the behavior of business decision makers is still an open question.

II. LITERATURE REVIEW

A. Decision Theories

Decision theory has a long history studying decision-making. Over last decades, decision-making has been studied from many different perspectives, however, managers experience difficulties applying new findings in practice [9]. Three main approaches to decision-making are normative, descriptive and prescriptive decision theories. Although each of them focuses on the value of decision outcomes, they are based on completely different assumptions and are evaluated by different criteria. Normative decision theory focuses on finding how people should make decisions and it is evaluated by theoretical adequacy (the degree to which it provides acceptable idealization or rational choice), whereas descriptive theory analyses how and why people think and act in the way they do. Descriptive models are evaluated by empirical validity (the extend to which they correspond to observed choices). In contrast to normative and descriptive theories, prescriptive models are looking for ways how to help people make better decisions and they are evaluated by pragmatic value (ability to help making better decisions) [10].

Normative approach of decision-making suggests some rules and standards for choice under risks. According to Shapira two main rules are expected value rule and expected utility rule [11]. Expected value is a weighted average of possible outcomes that are weighted by their probabilities. Expected value rule proposes to choose an alternative with highest expected value. This would mean that in case of having a 90% chance of winning $1000 and a 10% chance of winning $10, the expected value is 0.90*1000+0.10*10=901 which is better than having $900 with certainty. Bernoulli extends expected value rule saying that the value of an item must not be based on its price, but rather on the utility it yields (psychological value). He suggests that people make their decisions corresponding to the level of wealth and therefore expected value is the average of utilities of these outcomes weighted by probability. According to Bernoulli's logarithmic utility function wealthier people are emotionally less affected by a gain and will choose riskier alternatives. He also sets roots of the principle that is later known as the diminishing marginal utility of wealth by suggesting that any next increment of wealth is inversely proportionate to the amount of wealth already gained [12]. Jensen summarizes criticism of Bernoulli's approach expressing concerns about unbounded logarithmic function used as a utility function. He claims that utility function should be finite. Besides that Jensen questions why there are no other variables used together with expected value to determine preferences [13].

The later axiomatization of linear expected utility originated by von Neumann and Morgenstern sets fundamentals of expected utility theory. They prove that any rational individual whose preferences correspond to certain axioms (completeness [1], transitivity [2], independence [3], continuity [4]) will satisfy expected utility function thus endeavoring to gain maximum utility [14]. Expected utility theory has been not only accepted as normative model but also used as descriptive model of decision makers' behavior.

The strongest critique that hit an application of expected utility theory as a descriptive model at the fundamental level was provided by bounded rationality theory and prospect theory. In bounded rationality theory Simon explains rational choice taking into consideration cognitive limitations of the decision maker — limitations of both knowledge and computational capacity. He suggests that bounded by cognitive limitations decision makers look for satisfactory rather than optimal alternative [15]. According to Simon, decision-making comprises three principal phases:

- Intelligence - searching the environment for conditions calling for decision;
- Design - inventing, developing, and analyzing possible courses of action;
- Choice - selecting a particular course of action from those available [16].

Although prospect theory similarly to Bernoulli's expected utility theory analyses the psychological value of decision outcomes, it differs from expected utility theory in many fundamental ways. In prospect theory [17], originated by Kahneman and Tversky, choices that people make are assessed by S-shaped value function, which is concave for gains and convex and steeper for losses. The value of each outcome is multiplied by a decision weight that is inferred from choices between prospects. Decision weights depend primarily on the perceived likelihood of preference or event, but they are not probabilities. Contrary to Bernoulli's theory where utility of gain is assessed depending on the state of wealth, prospect theory contains three principles that influence the value of outcomes: neutral reference point, diminishing sensitivity principle and reflection effect [18].

Decision outcomes are usually perceived as gains and losses relative to a neutral reference point, which can be as well status quo as expected outcome. Outcomes that are better than reference point are gains but those that are worse than reference point are losses.

According to diminishing sensitivity principle the marginal value of both gains and losses generally decreases with their magnitude. This means that the difference between 100 and 200 is more significant than the same difference between 1100 and 1200.

As reported by the third principle - reflection effect – people are risk-seeking in choices between negative prospects, preferring loss that is merely probable over a smaller loss that is certain, whereas between corresponding positive prospects the certainty effect contributes to a risk-averse preference for a sure gain over larger gain that is merely probable. This means that in case of having 80% chance winning $4,000 or having $3,000 with certainty, the majority of people would prefer the latter option while in case of losing $4,000 with 80% probability or losing $3,000 with certainty, the majority would prefer the first choice.

Prescriptive decision theory focuses on application of normative and descriptive models to help solving real life problems. It analyzes one problem at a time looking for the best possible solution. Over the last decades prescriptive decision analysis has helped to solve myriad complex decisions. The purpose of prescriptive decision analysis is to provide insights to the best decision for a particular situation. Based on common sense and logical axioms decision analysis simplifies decisions by breaking them into parts but does not oversimplify the problem to be able to address the complexity of specific decisions [19].

Although there have been plenty of normative and descriptive researches of decision-making, there are serious research gaps in terms of a decision aider's interest. The gaps are of three types: specialty research, practice-driven research and aid development [20]. Although the awareness of behavioral aspects of decision-making has grown, behavioral issues have not received a great deal of attention by decision analysis researchers in recent years [21].

[1] The individual either prefers A to B, or is indifferent between A and B, or prefers B to A

[2] If A is preferred to B and B is preferred to C, then A is preferred to C

[3] If A is preferred to B, then an even chance to get A or C is preferred to an even chance to get B or C

[4] If A is preferred to B and B to C, then there should be a possible combination of A and C in which the individual is then indifferent between this mix and B

B. *Business Intelligence and Business Analytics*

Despite multiplicity of definitions of Business intelligence [22], typically Business intelligence and Analytics is seen as a set of methods, technologies and associated tools to improve business decision-making. Lately the term "Business Intelligence" is often being replaced by the term "Business Analytics". Analytics are not a new idea; it is possible to find references to corporate analytics as far back as the 1940s. Analytics began to command more attention in the late 1960s, when computers were used in decision support systems [23]. However, at that time data sources were relatively small and structured and the great majority of analytical activity was descriptive analytics [24]. Descriptive analytics (also called business intelligence (BI) or business reporting) is the entry level in analytics taxonomy. Most of the analytical activities at this level deal with creating reports to summarize business activities in order to report past or present status [25]. Data science first began to be discussed by academics around 2001 when Analytics 2.0 era began. In the early 2000s Big Data and advanced (predictive and prescriptive) analytics started to emerge in the commercial world [26] and the movement from traditional Business intelligence to real-time or right-time decision support data represented a true paradigm shift [27].

Big Data is still an emerging phenomenon but in recent past years its significance in different industries and countries has made it a pertinent research area for academic and management studies [28]. Although major innovations in analytical techniques for big data have not yet taken place, one anticipates the emergence of such novel analytics in the near future. For instance, real-time analytics will likely become a prolific field of research because of the growth in location-aware social media and mobile apps [29]. Despite the importance of Big Data, there is limited research on the use of Big Data Analytics for decision-making to date [30].

As the definition of the term "real time" varies from person to person, "right time" perhaps is a better term to describe the timely delivery of information to decision makers [31]. However, as we are talking about the moment when decision makers are making decisions, in our research we use the term "real time". There is a gap of research exploring if real time BI&A have any impact on cognitive constrains within decision makers and human information processing capabilities [32].

C. *Selective Perception*

What is even more important than the real-time analysis, are actions in response to analysis results that are performed in real time to change parameters of business processes instantaneously [33]. The longer time is spent between event occurrence and decision maker's action, the less impact the decision will have [34].

Dearborn and Simon in their early work wrote that managers process only certain information perceiving those aspects of the situation that relate specifically to the activities and goals of their department [35]. Several decades later J.P.Walsh extended Dearborn and Simon's study examining whether functional experience is incorporated in managers' belief structures, which may affect managerial information processing. However, his research results show little evidence of parochial information processing [36]. According to Schoemaker and Russo, most managerial decisions are still resistant to technological and conceptual advances [37]. Despite plenty of available information and technical solutions in large companies, according to Gigerenzer, in 50% of cases managers secretly base their business decisions on gut feeling. However, the lack of trust on their own or others gut feeling keeps executives away from following it [38]. Nevertheless, studies also show that less knowledgeable people, despite a lack of confidence on their financial savviness, very often would make more accurate financial decisions than intelligent computing systems or industry experts who have plenty of information available [39]. Schoemaker and Tetlock write that most organizations employ taboos that limit what managers can think, say, or do. Willingness to ignore dramatic scenarios often place organizations in situations where plans had not been made for what was in fact a predictable scenario [40].

D. *Theoretical Framework*

From one side research papers show that managers require data and information in their decision making process whereas from another side there are studies demonstrating that business decisions are frequently based on gut feeling ignoring available information. Despite fast technological progress in information gathering and displaying, managers still make their decisions based on gut feeling. They consider only information that is in accordance with their belief system. However, previous research papers lack focus on real-time information delivery. Whether managers would stick to their decisions if computer systems provided warnings about decision outcomes and made clear suggestions of changes in real-time – is still an open question. To fill the literature gap, inductive research with exploratory approach is performed. The main research question of the study is to find out how business decision makers respond to real-time BI&A warnings.

Figure 1 presents the theoretical framework of this research that results from the literature review. Our research will explore if real time BI&A warnings may impact and even change decisions linked to negative and positive prospects. Literature implies risk aversion in choices between positive prospects and risk seeking in choices between negative prospects. This leads to the formulation of the following hypotheses:

H1: Real-time BI&A warnings have low impact on the change of decision if predicted loss for alternative choice is smaller but certain.

H2: Real-time BI&A warnings have high impact on the change of decision if predicted loss for alternative choice is bigger but merely probable.

H3: Real-time BI&A warnings have high impact on the change of decision if predicted gain for alternative choice is smaller but certain.

H4: Real-time BI&A warnings have low impact on the change of decision if predicted gain for alternative choice is bigger but merely probable.

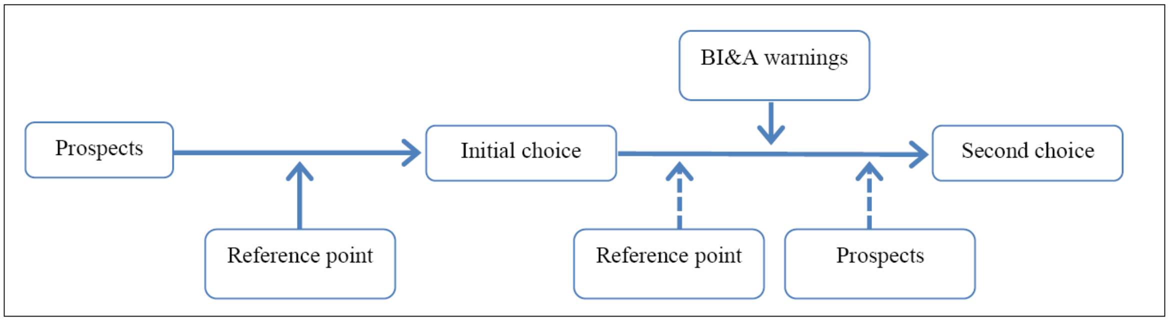

Figure 1. Theoretical framework

III. Method

Using two online experiments the authors of this research will explore if information delivery at the time when the business decision is being made influences or changes the decision maker's mind and leads to a different decision outcomes. First experiment will be conducted to test prospect theory having reference point different than zero. Second experiment will be conducted to explore if BI&A warnings have impact on second choice.

Participants of the first experiment will be asked to evaluate eight of twelve managerial problem scenarios. Each participant will be asked to make a choice in four scenarios of losses and four scenarios of gains. Mathematical expectancy of prospects and certainty equivalent will be calculated according to Tversky - Kahneman probability - weighting function [41].

In the second experiment participants will be asked to read a managerial problem scenario and then to communicate what they would do in the described situation. After submitting their decision, participants will receive BI&A warnings about estimated results of their decision and an opportunity to make a change.

The selection of MBA students having working experience appears to be an appropriate choice for the purpose of the research. To avoid student-manager surrogacy issues [42] experiments will be conducted on a sample of senior managers that will be used as a control group. Gender, age, GPA and education level are control variables measured directly together with industry where participants work in.

One potentially important threat affecting the validity of experimental social science research findings is social desirability bias [43]. One of techniques that reduce the social desirability bias is indirect questioning [44] or the use of proxy subjects [45]. Scenarios with proxy subject will be used for randomly selected participants and data will be analyzed to control validity of the research.

IV. Conclusion

Kahneman D. in his book "Thinking fast and slow" writes that we all would like to have a warning bell that rings loudly whenever we are about to make a serious error, but no such bell is available [18]. In organizational decision-making processes, however, very often it is possible to integrate predictive real-time BI&A warnings. How decision makers would respond to such warnings and would they really change their decision in case of receiving warning about decision consequences is still an open question.

Research concerning the impact of real time BI&A on cognitive constrains is missing. The research proposed here will be an important contribution to filling that gap. The research will contribute to descriptive and prescriptive decision theory and will add to existing literature in the field of business analytics and selective perception. Findings from online experiments will provide insights into the decision maker behaviour when warnings about decision consequences are given. Detected tendencies will provide data scientists with hints on how to better design BI&A systems to support decision makers.

References

[1] Gartner, Inc. (2017, February 17). Gartner Says Worldwide Business Intelligence and Analytics Market to Reach $18.3 Billion in 2017. Retrieved from https://www.gartner.com/newsroom/id/3612617

[2] Gartner, Inc. (2017). Mastering the New Business Executive Job of the CIO. Insights From the 2018 CIO Agenda Report. Retrieved from https://www.gartner.com/imagesrv/cio-trends/pdf/cio_agenda_2018.pdf

[3] Kielstra, P. (2007). In search of clarity Unravelling the complexities of executive decision-making. The Economist Intelligence Unit http://www.businessobjects.com/jump/emea/economist/report/EIU_In_search_of_clarity_8_August_2007.pdf

[4] Paradigm4. (2014, July 1). Leaving Data on the Table: New Survey Shows Variety, Not Volume, is the Bigger Challenge of Analyzing Big Data. Retrieved from http://www.prnewswire.com/news-releases/leaving-data-on-the-table-new-survey-shows-variety-not-volume-is-the-bigger-challenge-of-analyzing-big-data-265365761.html

[5] Gartner, Inc. (2015, September 15). Gartner Says Business Intelligence and Analytics Leaders Must Focus on Mindsets and Culture to Kick Start Advanced Analytics. Retrieved from http://www.gartner.com/newsroom/id/3130017

[6] Forrester Research, Inc. (2014, October). Boost The Value Of Your Enterprise BI With Advanced Search. Retrieved from http://go.thoughtspot.com/forrester-white-paper-0315.html

[7] Oracle. (2012, July 10). Big Data, Bigger Opportunities: Plans and Preparedness for the Data Deluge. Retrieved from http://www.oracle.com/us/industries/utilities/big-data-bigger-opportunities-study-1881351.pdf

[8] Columbia Business School. (2012, March 12). Study Finds Marketers Struggle with the Big Data and Digital Tools of Today. Retrieved from http://www.prnewswire.com/news-releases/study-finds-marketers-struggle-with-the-big-data-and-digital-tools-of-today-142312475.html

[9] Rosenzweig, P. (2013, November). What Makes Strategic Decisions Different. Retrieved from https://hbr.org/2013/11/what-makes-strategic-decisions-different

[10] Bell, D. E., Raiffa, H., & Tversky, A. (Eds.). (1988). Decision Making: Descriptive, Normative, and Prescriptive Interactions. Cambridge: Cambridge University Press.

[11] Shapira, Z. (1995). Risk Taking: A Managerial Perspective. New York: Russell Sage Foundation.

[12] Bernoulli, D. (1954). Exposition of a New Theory on the Measurement of Risk. Econometrica, 22 (1), 23-36.

[13] Jensen, N. E. (1967). An Introduction to Bernoullian Utility Theory: I. Utility Functions. The Swedish Journal of Economics , 69 (3), 163-183.

[14] von Neumann, J., & Morgenstern, O. (2007). Theory of Games and Economic Behavior. Princeton: Princeton University Press.

[15] Simon, H. A. (1982). Models of Bounded Rationality: Empirically grounded economic reason (Vol. 3). Cambridge: MIT Press.

[16] Simon, H. A. (1960). The New Science of Management Decision. New York: Harper & Row

[17] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47 (2), 263-292

[18] Kahneman, D. (2011). *Thinking, fast and slow*. New York: Farrar, Straus and Giroux.

[19] Keeney, R. L. (2004). Making Better Decision Makers. Decision Analysis , 1 (4), 193–204.

[20] Brown, R. V. (2006). Making decision research useful — not just rewarding. Judgment and Decision Making , 1 (2), 162–173.

[21] Wallenius, J., Dyer, J. S., Fishburn, P. C., Steuer, R. E., Zionts, S., & Deb, K. (2008). Multiple Criteria Decision Making, Multiattribute Utility Theory: Recent Accomplishments and What Lies Ahead. Management Science , 54 (7), 1336-1349.

[22] Foley, É., & Guillemette, M. G. (2010). What is Business Intelligence? International Journal of Business Intelligence Research , 1 (4)

[23] Delen, D. (2014). Real-World Data Mining: Applied Business Analytics and Decision Making. New Jersey: Pearson Education, Inc.

[24] Davenport, T. (2014). Big Data at Work: Dispelling the Myths, Uncovering the Opportunities. Harvard Business Review Press.

[25] Delen, D. (2014). Real-World Data Mining: Applied Business Analytics and Decision Making. New Jersey: Pearson Education, Inc.

[26] Davenport, T. (2014). Big Data at Work: Dispelling the Myths, Uncovering the Opportunities. Harvard Business Review Press.

[27] Wixom, B., & Watson, H. (2010). The Bi-Based Organization. International Journal of Business Intelligence Research , 1 (1), 13-28.

[28] Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. Journal of Business Research , 70, 263-286.

[29] Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management , 35, 137-144.

[30] Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. Journal of Business Research , 70, 338-345.

[31] Eckerson, W. W. (2010). Performance Dashboards : Measuring, Monitoring, and Managing Your Business. John Wiley & Sons, Inc.

[32] Nadj, M., & Schieder, C. (2016). Quo Vadis Real-Time Business Intelligence? A Descriptive Literature Review and Future Directions. 24th European Conference on Information Systems, (pp. 1-21). Istanbul, Turkey.

[33] Azvine, B., Cui, Z., & Nauck, D. D. (2007). Towards real-time business intelligence. BT Technology Journal , 25 (1), 214-225.

[34] Sauter, V. L. (2010). Decision Support Systems for Business Intelligence, 2nd Edition. John Wiley & Sons,Inc.

[35] Dearborn, D. C., & Simon, H. A. (1958). Selective perception: A note on the department identifications of executives. Sociometry , 21, 140-144.

[36] Walsh, J. P. (1988). Selectivity and selective perception: An investigation of managers' belief structures and information processing. The Academy of Management Journal , 31 (4), 873-896.

[37] Schoemaker, P. J., & Russo, J. E. (1993). A Pyramid of Decision Approaches. California Management Review , 36 (1).

[38] Gigerenzer, G. (2014). Risk Savvy: How to make good decisions. New York: Viking Press.

[39] Gigerenzer, G. (2007). Gut Feelings: The intelligence of the unconscious. New York: Viking Press.

[40] Schoemaker, P. J., & Tetlock, P. E. (2012). Taboo Scenarios: How to Think About the Unthinkable. California Management Review , 54 (2), 5-24.

[41] Kahneman, D., & Tversky, A. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty, 5 (4), 297-323

[42] Trottier, K., & Gordon, I. M. (2016). Students as surrogates for managers: Evidence from a replicated experiment. Canadian Journal of Administrative Sciences .

[43] Nederhof, A. J. (1985). Methods of coping with social desirability bias: a review. European Journal of Social Psychology , 15, 263-280.

[44] Fisher, R. J. (1993). Social Desirability Bias and the Validity of Indirect Questioning. Journal of Consumer Research , 20 (2), 303-315.

[45] Nederhof, A. J. (1985). Methods of coping with social desirability bias: a review. European Journal of Social Psychology , 15, 263-280.