


# The Effect of Individual Analytical Orientation and Capabilities on Decision Quality and Regret

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## ABSTRACT

Decision makers are exposed to an increasing amount of information. Algorithms can help people make better data-driven decisions. Previous research has focused on both companies' orientation towards analytics use and the required skills of individual decision makers. However, each individual can make either analytically based or intuitive decisions. The authors investigated the characteristics that influence the likelihood of making analytical decisions, focusing on both analytical orientation and capabilities of individuals. They conducted a survey using 462 business students as proxies for decision makers and used partial least squares path modeling to show that analytical capabilities and analytical orientation influence each other and affect analytical decision-making, thereby impacting decision quality and decision regret. The findings suggest that when implementing business analytics solutions, companies should focus on the development not only of technological capabilities and individuals' skills but also of individuals' analytical orientation.

## KEYWORDS

Analytical Orientation, Business Analytics, Decision-Making, Structural Equation Modeling, Tools and Technique Capabilities

## INTRODUCTION

Effective analysis and utilization of big data is a key factor for success in many business and service domains (Shukla & Mathur, 2020). In a context of scarce resources and profound change in customer needs, companies and individuals are faced with an abundance of decision possibilities (Kreuzer, Röglinger, & Rupperecht, 2020). Recommendation engines, filtering systems, prioritization and personalization algorithms have been tried to help individuals make better decisions and reduce their indecisiveness. Business analytics (BA) are increasingly being adopted in practice and emerging as an urgent challenge to improve personal and company performance, as evidence-based decision-making seems both desirable and rational (Beer, 2017; Holsapple, Lee-Post, & Pakath, 2014; Power, Cyphert, & Roth, 2019). Companies want to become more data-driven, specifically by taking advantage of real-time BA (Ain, Vaia, DeLone, & Waheed, 2019; Beer, 2017). BA provide a framework to exploit

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the synergies among fields such as data mining, quantitative methods, operations research, decision support system in a more practical format (Acharjya, Mitra, & Roy, 2019).

The interest of both academics and executives in investigating decision-making processes is longstanding (Ireland & Miller, 2004). The decision-making process needs to be better understood for organizations to create value from the use of BA (Sharma, Mithas, & Kankanhalli, 2014). The skillful use of BA by individual employees along with a culture of data-driven decision-making has the potential to radically improve companies' performance (Frisk & Bannister, 2017). The rise of smart manufacturing, the core idea behind the fourth industrial revolution (Industry 4.0), is generating more and more data that requires analysis. Recent advancements of several information technologies and manufacturing technologies, such as Internet of Things (IoT), big data, artificial intelligent (AI), cloud computing, cyber-physical systems, digital twins, among others, have leveraged the development and use of business analytics capabilities and an orientation to make decisions based on such data by individuals and organizations (Dhamija, Bedi, & Gupta, 2020; Jagatheesaperumal, Rahouti, Ahmad, Al-Fuqaha, & Guizani, 2021; My, 2021; Rowlands & Milligan, 2021; Sahu, Sahu, & Sahu, 2020).

Information is recognized to play a key role by enhancing and providing insights to improve decision-makers' performance (Tang & Liao, 2021). There are two main ways for an individual to process information, one being considered intuitive, natural, automatic and experiential and the other logical-conceptual, analytical-rational, explicit, systematic and intentional. Analytical orientation is characterized by an individual's thinking that is oriented by data, reason and logical connections. The experiential or intuitive orientation, in turn, can be characterized as more holistic, experiential, dissociative, oriented to immediate actions and emotional (Epstein, Pacini, Denes-Raj, & Heier, 1996; Tversky & Kahneman, 1983). Some of the past research argued that much of cognition occurs automatically outside of consciousness and in the realm of intuition (Agor, 1986; Sadler-Smith & Shefy, 2004).

Rational behavior has a central place in decision-making theory and practice (Papadakis & Barwise, 1997). Despite the existence of several seminal studies on rationality in decision-making processes (Dean & Sharfman, 1993; Eisenhardt & Zbaracki, 1992; Simon, 1979), the relationship between rationality and decision performance needs more clarification (Božič & Dimovski, 2019). Further, analysis in Ain et al. (2019) showed that human factors have largely been ignored in BA studies, which are mainly limited to either organizational or information systems-related factors. The research has not sufficiently covered all relevant levels of analysis, as there is a dearth of research on effective BA use (Trieu, 2017). Moreover, no studies have directly addressed the effects of analytical orientation and analytical capabilities on both decision quality and regret about a decision. In summary, there is no consolidated knowledge yet about the BA value creation process (Božič & Dimovski, 2019).

The aim of this paper is to empirically investigate analytical capabilities and analytical orientation as components of analytical decision-making (using an analytical approach) by individuals. We also investigate whether such decision-making has positive effects on the quality of decisions made by individuals as well as on the reduction of decision regret. We use a sample of 462 business administration students to test our proposed model.

The paper is divided into six sections, including this introduction. The second section presents the theoretical framework, which exposes the associations between analytical capabilities, analytical orientation, decision regret and decision quality. The hypotheses are presented in the third section of the manuscript, and the research method follows in the fourth section. The fifth section presents the results, followed by the research limitations and further research topics.

## **THEORETICAL FRAMEWORK**

BA is defined as the use of data to make sounder, more evidence-based business decisions enabled by IT-based tools (e.g., data warehouses, online analytical processing [OLAP] and statistical, visualization and data mining tools) (Seddon, Constantinidis, Tamm, & Dod, 2017). BA is a holistic approach

to managing, processing and analyzing the various data-related dimensions (Fosso Wamba, Ngai, Riggins, & Akter, 2017). The approach, seen as a combination of people's analytical capabilities and analytical orientation that drives processes and the use of multiple information technologies for accessing and treating large amounts of structured and unstructured data, is aimed at generating descriptive, predictive and prescriptive models (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Chen, Chiang, & Storey, 2012; Jamehshooran, Shaharoun, & Haron, 2015).

BA requires a set of technologies, advanced analytical tools and methodologies. However, a fundamental part of the effectiveness of BA depends on the abilities of individuals to extract, store, integrate, transform and disseminate relevant data as well as to inform others or use that information to support decision-making processes. The success of BA projects requires not only infrastructure, knowledge and tools for dealing with data but also an understanding of how BA translates to better decision-making (Barton & Court, 2012; Chae & Olson, 2013; T. H. Davenport, 2013; T. H. Davenport & Patil, 2012; Kiron, Prentice, & Ferguson, 2014).

In general, BA capabilities are considered as a new type of organizational capability (W. Y. C. Wang & Wang, 2020) and are described through at least three perspectives, those being the organizational (managerial analytical approach), physical (IT infrastructure) and human (skills and knowledge) perspectives. Regarding the specific human dimension, certain works (Akter et al., 2016; Gupta & George, 2016) emphasize the technical skills and proficiency of individuals with modeling tools or expertise in data management. Popovic et al. (2012) identified the skills of the individual in producing and exploring different tools and techniques. Therefore, any description of a firm's analytical capabilities will involve a human approach in addition to managerial and technological dimensions (Barton & Court, 2012; T. H. Davenport & Patil, 2012; Kiron et al., 2014).

Most previous research (Holsapple et al., 2014; Mello & Stank, 2005; Noble, Sinha, & Kumar, 2002) has either explicitly or implicitly studied analytical orientation/capabilities at the organizational level. An additional research stream has examined the skills needed for business analysts and identified skills such as domain knowledge, organization, communication, information management, machine learning, statistics, mathematics, computing and operations research and structured data management (Akhtar, Frynas, Mellahi, & Ullah, 2019; Cegielski & Jones-Farmer, 2016; Dubey & Gunasekaran, 2015; Verma, Yurov, Lane, & Yurova, 2019).

In this sense, within a firm context, analytical capabilities and analytical orientation can affect positively the quality of decisions for several reasons: both conditions may lead individuals to leverage their knowledge about the variables of a certain problem, or to access the required inputs for the decision, or even a greater ability in recognizing relevant associations between the variables involved in the decision (Côte-Real, Oliveira, & Ruivo, 2017; Ghasemaghaei, Ebrahimi, & Hassanein, 2018; Lee, 2001; Raghunathan, 1999).

We argue that while analytical capabilities and analytical orientation are both extremely important, the knowledge gained on the subject is still insufficient. Every individual possesses a certain level of tool expertise and personal inclinations that influence how he or she is inclined to use available data when making decisions (Khanra, Dhir, & Mäntymäki, 2020). Therefore, the definition and measurement of individual analytical orientation and analytical capabilities are crucial to better understand the human dimension of BA.

All this means that studying individual analytical orientation is of the utmost importance. To enable its investigation, we conceptualize an individual's analytical orientation by following the definition of a firm's orientation, which has been considered as an overall problem-solving approach to strategic decision-making (Morgan & Strong, 1998); as a compromise to search deeper for the roots of problems and to make good use of appropriate management systems, such as information and control systems (Venkatraman, 1989); and as a trait of an analytics-focused organization, which channels its resources into BA initiatives that foster the firm's ability to collect, analyze and act on data (T. H. Davenport, 2013, 2014).

When facing complex problems with considerable impacts on their lives, individuals can turn to an analytical thinking pattern of processing information, using analytical tools and techniques, seeking as much data as possible and employing a reasoning process before taking a proper action. In this sense, both analytical orientation and analytical skills are required to take advantage of the available information to reach better decisions.

## RESEARCH HYPOTHESES

Although concepts such as analytics capability and analytics technology have been used in prior studies, the elements of these concepts are still unclear (Krishnamoorthi & Mathew, 2018). BA capability is a multidimensional construct formed by capturing the functionalities of BA systems and continued from data extraction and data analysis to visualization and reporting (Y. Wang & Byrd, 2017). Thus, analytical decision-making is considered in our study as a combination of individuals' analytical orientation and capabilities due to the tendency of individuals to follow normative rational principles in their decision-making processes (Ceschi, Demerouti, Sartori, & Weller, 2017; Geisler & Allwood, 2018).

Tools and technique capabilities (TTC) include tools that support traditional ad hoc queries, inferential statistics, predictive analytics, simulation and optimization, thus supporting descriptive, diagnostic, predictive and prescriptive analytics (Acito & Khatri, 2014). Analytical tools are a fundamental part of any BA system (Sun, Strang, & Firmin, 2017), as a wide array of BA tools must be available to decision-makers (Wixom, Yen, & Relich, 2013).

While data scientists undoubtedly need strong statistical and mathematical skills, they also need IT skills—notably an ability to program (e.g., R) and an ability to manipulate data (e.g., SQL) (Vidgen, Shaw, & Grant, 2017)—to develop higher analytical capabilities (Acito & Khatri, 2014). Thus, individual IT competencies—namely, IT-related skills, IT knowledge and utilization ability—are crucial for analytical capabilities (Ain et al., 2019).

This leads to our first hypothesis:

**H1:** Tools and techniques are a constituent of analytical capabilities.

Although technology is important, it represents only one of many challenges that individuals must address if they are to become data-driven (Vidgen et al., 2017). Personal biases and emotional processes (both conscious and unconscious) affect the processing of cognitive and emotional responses (Xu et al., 2020). Human subjectivity may also affect data preparation, algorithm design, and interpretation of the outputs (Khanra et al., 2020). There is a fundamental structure to data-analytic thinking and to basic principles of causal analysis, along with particular areas where intuition, creativity, common sense and knowledge of a particular application must be understood (Provost & Fawcett, 2013). Individuals can benefit more from BA by using both inductive and deductive reasoning (Erevelles, Fukawa, & Swayne, 2016). Thus, the exploration of users' perception is important (Ain et al., 2019).

This leads to our second hypothesis:

**H2:** Inductive and deductive reasoning are constituents of analytical capabilities.

There are different complementary conceptualizations of rationality in the literature. It has been seen as a systematic process for reaching carefully thought-out goals (Schwenk, 1995), as a behavior understandable within a given frame of reference (Butler, 2002), and as a decision process involving the collection of information relevant to a decision and the reliance upon analysis of that information in making a choice (Dean & Sharfman, 1996). In summary, rationality can be considered as an explicit (formal), systematic and analytical approach to decision-making (Khatri, 1994).

From these considerations, we argue that analytical decision-making is a combination of both analytical orientation and analytical capabilities. We thus base the next three hypotheses on this understanding.

With scarce resources and profound change in customer needs (Kreuzer et al., 2020), companies and individuals are faced with an abundance of decision possibilities and uncertainty about how to decide and, therefore, react. For the aims of this research, we rely on IPT (Information Processing Theory) (Galbraith, 1973, 1974, 2014). Regarding IPT, “the greater the uncertainty of the task, the greater the amount of information that has to be processed between decision-makers during the execution of a task” (Galbraith, 1974, p. 28). Based on IPT, we propose that professionals need strong quantitative and analytical skills to understand and respond to current environmental challenges; thus, the development of data analysis skills is crucial (Bravo et al., 2016). Following IPT, we assume that an individual’s analytical capabilities can modify the way he or she perceives and reacts to events. In this sense, it is not the data per se that affect the individual’s judgment or behavior in decision-making, but the individual’s ability to access and process relevant data into useful information necessary for decision-making. This leads to the third hypothesis:

**H3:** Analytical capabilities positively affect analytical decision-making.

An analytical decision-making culture is crucial to improving the use of information (Popovič et al., 2012). With greater computational information processing capacity and an analytical approach, BA can extend humans’ cognition while augmenting but not replacing human contributions (Jarrahi, 2018). Finally, an analytical decision-making orientation transmits positive effects to use data and facts systematically and analyze them for decision-making tasks (Kulkarni, Robles-Flores, & Popovič, 2017). This leads to the fourth hypothesis:

**H4:** Analytical orientation positively affects analytical decision-making.

While we argue that analytical capabilities and analytical orientation are two distinct constructs, there are obviously correlations between them. It is important to study how orientations influence performance differently when leveraged through capabilities (Sinkovics & Roath, 2004), and the correlation of capabilities and orientations (Demirkan & Delen, 2013) needs to be understood much better.

This leads to the fifth hypothesis:

**H5:** Analytical capabilities and analytical orientation are correlated.

The core purpose of BA is to support decision-making (Holsapple et al., 2014; P. Trkman, McCormack, de Oliveira, Ladeira, & Oliveira, 2010). It is thus crucial to study how BA facilitate data-driven decision-making (Cao, Duan, & Li, 2015), as one of the main benefits of BA is better decision-making (Wixom et al., 2013). The first and foremost effect of BA should be on decision quality (Sharma et al., 2014). This leads to the sixth hypothesis:

**H6:** Analytical decision-making positively impacts decision quality.

In general, there is a lack of research on how analytical decision-making, confidence and uncertainty are related. It is known that when making decisions, individuals anticipate regret and try to avoid it (Buchanan, Summerville, Lehmann, & Reb, 2016), but it is also important to consider that the inherent uncertainty within BA tools can lead to a lack of confidence in the resulting decisions made thereof (Hariri, Fredericks, & Bowers, 2019; Khanra et al., 2020). Previous studies on the

effect of analytical decision-making on decision regret had conflicting results. On the one hand, it can be expected that people who spend energy, time or money to make analytical decisions may experience dissatisfaction or regret later (Moyano-Díaz, Martínez-Molina, & Ponce, 2014). Further, BA decision-making can introduce uncertainties additional to those inherent in the data and result in impaired decision-making, with human biases influencing the awareness of such uncertainties (Sacha, Senaratne, Kwon, Ellis, & Keim, 2016).

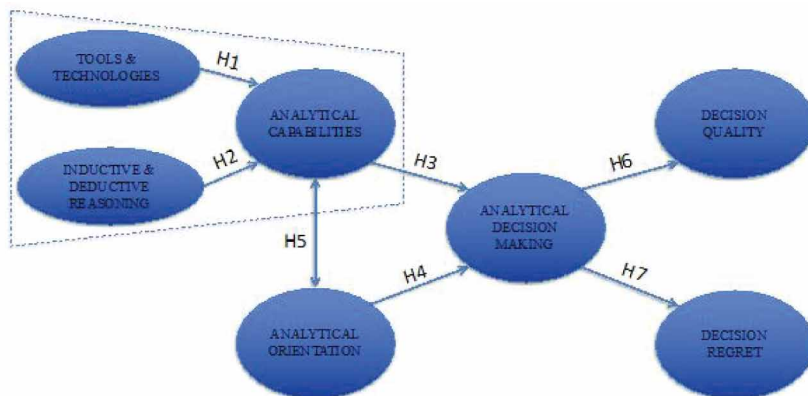
However, analytical decision-making can help specifically in detecting, anticipating and responding strategically, thus helping one realize opportunities and reduce regret (van Rijmenam, Erekhinskaya, Schweitzer, & Williams, 2019). Accordingly, the regret minimization paradigm has been attracting increased interest (Masiero, Yang, & Qiu, 2019). Decision makers are likely to strive to minimize anticipated regret by utilizing BA to recommend optimal solutions (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017).

Moreover, especially in cases where individuals are not forced to use a particular BA tool but can work with experience-based BA tools, analytical decision-making should be beneficial for regret reduction (Viaene & Van den Bunder, 2011). This leads to our seventh and last hypothesis:

**H7:** Analytical decision-making reduces decision regret.

Based on these assumptions, the structural model that was tested in this research is presented in Figure 1.

Figure 1. Structural model proposed



## MODEL SPECIFICATION AND OPERATIONALIZATION

The analytical capabilities (AC) were conceptualized as a second-order construct consisting of two first-order constructs: TTC (tools and technique capabilities), which are individuals' technological skills, and IDR (inductive and deductive reasoning), which are individuals' cognitive skills.

To assess capabilities related to analytical tools and techniques (TTC), we measured the respondents' perceptions of how easy it would be to use tools to describe what is happening, predict what is going to happen and prescribe what should be done (Acito & Khatri, 2014; Chen et al., 2012; T. H. Davenport, 2014; Delen & Demirkan, 2013; Holsapple et al., 2014). Moreover, we asked respondents to inform us how often they use modeling techniques to represent and solve problems

(Chen et al., 2012; Delen & Demirkan, 2013; Gorman & Klimberg, 2014; Holsapple et al., 2014; Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

For inductive and deductive reasoning (IDR), we asked respondents how easy they thought it would be to use evidence/facts to recognize problems and find the right data, prepare it for analysis, exploit it, and make use of critical reasoning to support important decisions (Delen & Demirkan, 2013; Demirkan & Delen, 2013; Gorman & Klimberg, 2014; Holsapple et al., 2014; Muehlen & Shapiro, 2010; Taylor, 2015).

We measured the analytical orientation (AO) construct by considering analytical thinking as a cognitive process (Evans, 2008) and used perceptual questions to measure how often, when making important decisions, the respondents use analytical models, consider data as important, analyze data and externally collect data and user reviews (Cosic, Shanks, & Maynard, 2012; Lavalle, Hopkins, Lesser, Shockley, & Kruschwitz, 2010).

Decision regret is the emotion experienced by an individual upon realizing or imagining that his or her current situation would have been better if he or she decided differently, and it signals an unfavorable evaluation of a decision (Pieters & Zeelenberg, 2007). To assess decision regret, we relied on decision justification theory, which postulates that the overall feeling of regret is a combination of two core components: one associated with comparative evaluation of the outcome (“I am often concerned about my important decisions after they are made”) and the other with the feeling of self-blame for having made a poor choice (“I often must reverse course on an important decision because I was wrong”) (Connolly & Zeelenberg, 2002).

Finally, we used the self-reported assessment of decision quality (“I generally make good important decisions” and “I have confidence in my important decisions”).

## Research Design

We tested the hypotheses through a survey that collected information on the perceptions of undergraduate students regarding the impact of BA use on both the quality of and regret over their decisions. Four hundred sixty-two business administration students from Slovenia and Brazil replied to the survey. The practice of using students is convenient and provides researchers with large, readily accessible pools of participants (Compeau, Marcolin, Kelley, & Higgins, 2012). This is especially true for business analytics field which poses many opportunities for the education sector (S. Wang & Wang, 2020). Further, we were interested in the general orientation and perception of individuals, so using a sample of similar individuals who had not yet been exposed to analytically based training was best. Similarly to Trkman et al. (2019), those students were good proxies for junior analysts. The described group of students was an appropriate approximation of real-world decision makers with respect to personality and education/knowledge, apart from them lacking the experience that real-world managers have (Strohhecker & Größler, 2013).

For Slovenian and Brazilian students, we administered the survey at the start of computer labs where the students had to be present. This reduced the risks of non-response bias, which is an important concern in administering surveys with the Internet and via e-mail (Wells, Cavanaugh, Bouffard, & Nobles, 2012). Sufficient time was allocated for answering the set of questions. Participation was voluntary, and the students had the right to withdraw at any time. They did not receive course credits or other benefits for participation. The goals and hypotheses of the research were not explained to the participants to reduce the likelihood of biases.

We initially examined the data set for equivalence (i.e., to determine if students from different countries responded to questions in a similar fashion). Ignoring equivalence issues can lead to ambiguous or erroneous conclusions (Knoppen et al., 2015). To test configural, metric and scalar equivalence, the PLS-MGA test was conducted in accordance with the recommendations of Knoppen et al. (Knoppen et al., 2015), who argue that multigroup analysis (MGA) is the best approach to test equivalence. PLS-MGA, an extension of the original MGA method of Henseler et al. (2009), showed no equivalence problems between groups. Configural equivalence was checked, with all indicators

loading significantly on the same factors across groups. In a similar manner, a metric equivalence test showed no statistical differences between factor loadings across groups, with all p-values in the range of 0.05 to 0.95 (Sarstedt, Henseler, & Ringle, 2011).

## RESULTS

Partial least squares path modelling (PLS-PM) (Sanchez, 2013) was used to evaluate the hypothetical model (Figure 1) with the R software (R Core Team, 2016). The PLS algorithm was chosen because it requires no assumptions about the data distribution (Hair, Hult, Ringle, & Sarstedt, 2017). As the questionnaire was based on a 5-point scale and ordinal scales with few scale points increase skewness and kurtosis, detection of normality was not relevant (Leung, 2011). Moreover, PLS results are considered good proxies for CB-SEM (which does require normality) results and are therefore deemed a good methodological alternative for theory testing when CB-SEM assumptions are violated (Hair et al., 2017). PLS-PM for R was chosen because it was the only path modelling tool that would allow users to set manifest variables as ordinal ones. We assessed model fit by using GoF,  $R^2$  and bootstrapping results for path coefficients.

In assessing the measurement models, we assumed all of them to be reflective on the basis of all manifest variables being related to outcomes in the presence of each respective construct. Internal consistency was checked by examining unidimensionality measures (Dillon-Goldstein's rho). The rule of thumb for Dillon-Goldstein's rho is to consider a block as unidimensional when values are larger than 0.7. The results showed that all constructs passed the unidimensionality test. Finally, we tested discriminant validity by examining cross-loading analysis and by the Fornell-Larcker criterion. Both tests indicated no problems with discriminant validity in the measurement models.

The model specification with 462 cases included seven latent variables and 19 manifest variables scaled as ordinal ones. The centroid-weighting scheme was used with a tolerance criticality of  $1e-06$ . The model converged after 28 interactions.

The latent variables of analytical capabilities (AC) and analytical decision-making (ADM) were considered as high-order constructs—the former second- and the latter third-order—and were modelled by using the Repeated Indicators approach (Sanchez, 2013).

Assessment of the structural model was conducted by inspecting the results of each regression in the structural equations that follow:

$$\text{Analytical Decision-Making (ADM)} = 0.748 * \text{AC} + 0.458 * \text{AO} + \text{Error} \quad (1)$$

$$\text{Decision Quality} = 0.255 * \text{ADM} + \text{Error} \quad (2)$$

$$\text{Decision Regret} = 0.223 * \text{ADM} + \text{Error} \quad (3)$$

The intercepts for all equations were not significant, and all beta values shown in the equations were found to be significant with a p-value  $< 0.001$ . Besides the results of the regression equations, we evaluated the quality of the structural model by examining the  $R^2$  determination coefficients, the redundancy index and the goodness-of-fit index (GoF = 0.4399). The structural model displayed a high goodness of fit and good quality scores, as shown in Table 1.

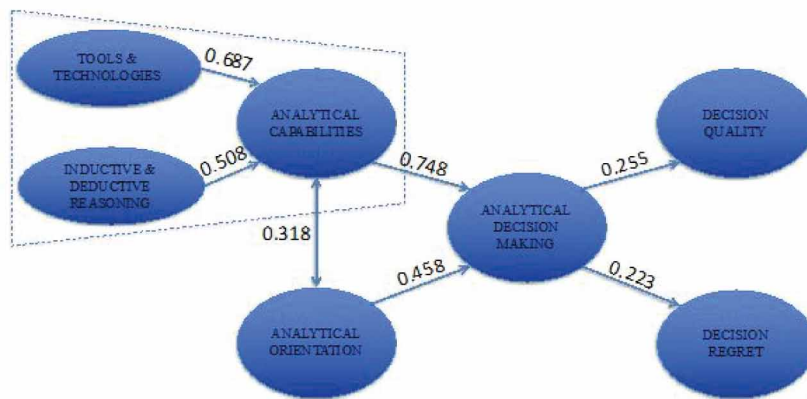
Bootstrapping was used to obtain confidence intervals to evaluate the precision of the PLS parameter estimates. As all bootstrap intervals for the path coefficients were non-zero, we may confidently state that the path coefficients of the research model were significant at a 5% confidence level (Sanchez, 2013).



Table 1. Summary of model estimates

Construct	R <sup>2</sup>	Block	Mean	Average Variance Explained
		Communality	Redundancy	
AC	0.999	0.340	0.339	0.340
AO	0	0.397	0	0.397
AT	0.986	0.246	0.243	0.246
DQ	0.065	0.677	0.044	0.677
DR	0.050	0.461	0.023	0.461

Figure 2. Model with statistically significant coefficients (p-value < 0.05)



The correlations between AC and AO and between DQ and DR were also computed. Pearson’s product-moment correlation between AC and AO was proven to be significant (p-value < 0.001), scoring 0.318.

Furthermore, Table 2 shows the direct and indirect effects of analytical orientation and analytical capabilities on decision quality and decision regret. The  $f^2$  effect shows whether the omitted construct has a substantive impact on the endogenous constructs.

Table 2.  $f^2$  effects

	R <sup>2</sup> full	R <sup>2</sup> without Analytical Capabilities	R <sup>2</sup> without Analytical Orientation	$f^2$ without Analytical Capabilities	$f^2$ without Analytical Orientation
Decision Quality	0.0652	0.0447	0.0532	0.02192982	0.01283697
Decision Regret	0.0495	0.0629	0.0267	-0.0140978	0.02398738

The  $f^2$  effect analysis assesses the importance of the exogenous constructs to explain the endogenous constructs. The  $f^2$  values of 0.02, 0.15 and 0.35 respectively represent small, medium and large effects (Cohen, 1988) of the exogenous latent variable. Table 2 shows that while the inclusion of the analytical orientation construct helps improve the R<sup>2</sup> of both the decision quality and the decision

regret constructs, the analytical capabilities construct helps improve the decision quality's  $R^2$  and decrease the decision regret's  $R^2$ .

Random Forest Regression, a type of bagged estimate based on decision tree models (Bruce & Bruce, 2017), was used to identify the most important variables influencing Decision Quality and Decision Regret. By having Decision Quality as the target, the Random Forest Regression model was estimated (500 trees, 8 variables per split, MSE 1.65, and %Variance explained of 4.24). By considering both Mean Decrease Accuracy and Gini measures, the most important measures were about how easy is to find the right data to support important decisions, followed by the abilities to use prescriptive tools and modeling techniques to represent and solve problems. By having Decision Regret as the target, the Random Forest Regression model was estimated (500 trees, 8 variables per split, MSE 0.09, and %Variance explained of 94.35). By considering both Mean Decrease Accuracy and Gini measures, the most important measures were about how easy is to make use of critical reasoning when making important decisions, followed by the orientation to make important decisions analyzing data, modeling techniques to represent problems, and exploit the right data to support important decisions. In general, it could be observed that Analytical Orientation is more important to Decision Regret than to Decision Quality. In this sense, to assure decision quality, analytical capabilities are of utmost importance. But, to avoid decision regret, analytical capabilities will not be as relevant without proper analytical orientation.

Such findings open a new and important avenue for investigation to understand the role of analytical capabilities in reducing decision regret. Our results suggest that while both analytical orientation and analytical capabilities can help explain decision quality, the former can be a necessary but not sufficient condition to explain regret. In other words, an analytically oriented decision, grounded by analytical capabilities, could be depicted as helping reduce decision regret. On the other hand, when analytical capabilities are not considered, a decision can be subject to stronger judgement by analytically oriented decision makers, causing regret to vary. In such terms, it can be assumed that when companies make any investment to improve decision quality and reduce decision regret, they should ensure proper analytical capabilities are in place and aligned with their analytical orientation.

## DISCUSSION AND CONCLUSION

Many organizations today are attempting to increase the use of analytics in decision-making. Analytics has been shown to improve business performance in almost every economic segment, so there are incentives driving this effort. How do analytics involve individuals within the organization? What factors influence the use of analytical models? This research has attempted to define and test the factors involved in this process and to answer questions on how to help an organization effectively increase its analytical decision-making, which improves decision quality and reduces regret.

Analytical capabilities and analytical orientation influence each other and both affect analytical decision-making. This research suggests that the more analytical capabilities people acquire, the more analytically oriented they become. They see the value and utility of using data and models to help in making decisions. Analytical capabilities seem to impact analytical decision-making more than analytical orientation, but they both have a positive impact. It would be reasonable to think that as a pathway for individuals to take greater advantage of analytical decision-making, one should invest in developing analytical capabilities, which would help develop a superior analytical orientation in the individual and leverage improved quality and reduced regret in decision-making.

Analytical capabilities have been shown to be made out of a balance of cognitive and technical capabilities (respectively, the dimensions of "inductive and deductive reasoning" and "tools and technologies"). Both dimensions are relevant to explaining the variability of model-dependent constructs. If an organization wants to improve its use of analytics, it obviously must train members in the tools and techniques to be used and in "reasoning" approaches.

This research has shown that analytical capabilities and analytical orientation are both important factors in analytical decision-making and therefore impact decision quality and regret. In this sense, when an individual improves in one of those two constructs, the other construct will also be improved, and improvements in analytical decision-making will consequently deliver regret reduction and improved quality of outcomes.

This research has shown that an increase in analytical decision-making reduces regret. Under this condition, people are more confident in their decisions. With the availability of the smartphone and Internet access everywhere, people are becoming more capable and confident with using data in decisions, which will impact decision-making in organizations that are increasing the effective use of analytics. Reducing decision regret or increasing confidence in using data in decisions will help organizations become more analytically oriented and capable as well as improve the quality of their decisions. This progress will also have an impact on society in general by moving people toward analytical decision-making and better decisions.

Our study has limitations that constrain a broad generalization of its findings. We used students and not decision-making professionals as research subjects. However, our research is consistent considering the perspectives of the individuals. As good proxies for junior analysts, the students mitigated the impact of not studying decision-making professionals directly. Another limitation of our study is that we made use of non-validated questionnaires. We acknowledge that self-reported data to measure decision quality could be biased in various ways. Although the survey instrument met certain formal prerequisites, the use of interviews or experiments would be beneficial in future studies.

Further research should repeat the study with employees working on real business problems. Further constructs could be investigated to increase the explanatory power of the model. Another area of future research could be investigation of how training can influence analytical capabilities and orientation. This could also be studied at the firm level, recognizing how companies can implement a data-analytical culture, establish a data strategy and leverage their analytical capabilities over time.

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## APPENDIX

**Table 3. Questionnaire / Constructs**

Tools & Technologies	If you were required, how easy it would be to: Use tools (i.e. Excel, Power BI, Tableau) to describe what is happening
	If you were required, how easy it would be to: Use tools (i.e. Excel, Power BI, Tableau) to predict what is going to happen
	If you were required, how easy it would be to: Use tools (i.e. Excel, Power BI, Tableau) to prescribe what should be done
	If you were required, how easy it would be to: Use modeling techniques (i.e. Excel templates, etc.) to represent problems
	If you were required, how easy it would be to: Use modeling techniques (i.e. Excel templates, etc.) to solve problems
Inductive & Deductive Reasoning	If you were required, how easy it would be to: Find the right data to support your important decisions
	If you were required, how easy it would be to: Prepare the right data to support your important decisions
	If you were required, how easy it would be to: Exploit the right data to support your important decisions
	If you were required, how easy it would be to: Make use of critical reasoning when making important decisions
	If you were required, how easy it would be to: Use evidences/facts to recognize problems
Analytical Orientation	I make important decisions by analyzing data.
	I think that data is very important to my life.
	I use analytical models (simple or complex) when making important decisions.
	I often use “user reviews” (i.e. Yelp) when making an important decision.
	I usually search for data when considering an important decision
Decision Quality	I generally make good important decisions.
	I have confidence in my important decisions.
Decision Regret	I often must reverse course on an important decision because I was wrong
	I am often concerned about my important decisions (hang over) after they are made.

Note: Analytical Capabilities and Analytical Decision Making were taken as high-order constructs.

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