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The Impact of Business Intelligence and Analytics Adoption on Decision Making Effectiveness and Managerial Work Performance

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Abstract: Business Intelligence and Analytics systems have the capability to enable organizations to better comprehend their business and to increase the quality of managerial decisions, and consequently improve their performance. Recently, organizations have embraced the idea that data becomes a core asset, and this belief also changes the culture of the organization; data and analytics now determine a data-driven culture, which makes way for more effective data-driven decisions. To the best of our knowledge, there are few studies that investigate the effects of BI&A adoption on individual decision-making effectiveness and managerial work performance. This paper aims to contribute to bridging this gap by providing a research model that examines the relationship between BI&A adoption and manager's decision-making effectiveness and then his individual work performance. The research model also theorizes that a data-driven culture promotes the BI&A adoption in the organization. Using specific control variables, we also expect to observe differences between different departments and managerial positions, which will provide practical implications for companies that work on BI&A adoption.

Keywords: Business Intelligence and Analytics; data-driven culture; decision-making effectiveness; individual work performance.

JEL classification: M15; D81; L86.

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1. INTRODUCTION

Data-driven culture is increasingly embraced by organizations that become aware of the benefits of this approach. An insight from Assur and Rowshankish (2022), suggestively entitled "The data-driven enterprise of 2025," affirmed that "the data-driven culture fosters continuous performance improvement to create truly differentiated customer and employee experiences," given the multitude of cutting-edge new technology that constantly become available.

In recent times, Business Intelligence and Analytics (BI&A) has developed as a representative field in Decision Support Systems research and attracted significant interest in academia. In the current dynamic environment and economic uncertainty, Chen *et al.* (2012) insinuated that they will successfully transform the organizational decision-making process. Having in mind the importance of decision making in managers' work, Sharda *et al.* (2015, p. 615) emphasize the significant role of analytics systems that will transform their job because they are able to "change the manner in which many decisions are made." The same authors (2015, p. 616) consider that "analytics technologies tend to reduce the time required to complete tasks in the decision-making process and eliminate some of the nonproductive waiting time by providing knowledge and information." Given the Big Data challenge that companies have to face, accurate and pertinent decisions are only possible with BI&A that offer the tools to analyze large volumes of data (Trkman *et al.*, 2010).

Studies on the effects of using BI&A systems have shown that their usage enhance organizational performance. Some authors have attested a direct relationship with operational performance (e.g., Anderson-Lehman & Watson, 2004; Trkman *et al.*, 2010; B. Chae *et al.*, 2014; Appelbaum *et al.*, 2017), others explain that BI&A contributes to business performance by creating value (e.g., Sharma *et al.*, 2010; Wixom *et al.*, 2013; e.g., Seddon *et al.*, 2017). As regards individual perception, traditionally (starting with DeLone & McLean, 1992) there are studies that analyze 'user satisfaction about the information system' as a construct that affects individual performance (i.e., decision effectiveness, problems detection, or individual work productivity). However, few papers analyze the impact of BI&A on individual work performance; for example, there is evidence of higher individual work performance determined by the use of BI (Hou, 2012). Our paper aims to contribute at filling this research gap, by analyzing the effects of BI&A adoption on managerial work performance. The targeted individuals are managers at different organizational levels that work in different departments.

While there is evidence that BI&A adoption has effects on organizational performance, we want to demonstrate that the decision-making process itself is positively affected. Furthermore, we want to validate that there is a positive relationship between a data-driven culture in the organization and BI&A adoption. Therefore, we formulate the following research questions:

RQ1. Does the data-driven culture promote the adoption of BI&A in an organization?

RQ2. To what extent the adoption of BI&A influences the effectiveness of decision-making and thus the managerial work performance?

2. LITERATURE REVIEW

2.1 Data-driven culture

The data-driven organizations are the ones that have managers that realize the benefits of trusting on data insights to take intelligent business actions. According to the results of a McKinsey Global Institute study cited in Bokman *et al.* (2014), the data-driven organizations "are 23 times more likely to acquire customers, six times as likely to retain customers, and 19 times as likely to be profitable as a result." The worldwide phenomenon of ongoing data growth and the more and more digitalized reality generated a new tendency in organizational management known as 'data-oriented' or 'data-driven' approach, described as a "strategic process of leveraging insights from data" to improve performance and gain competitive advantage (De Saulles, 2019). With this new line of action, managers are able to use "evidence-based data" when making their decisions (De Saulles, 2019).

Kiron *et al.* (2013) gave one of the first definitions of data-oriented culture as "a pattern of behavior and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a crucial role in the success of the organizations." Holsapple *et al.* (2014) acknowledged this definition and enhance it by indicating that it should be "consistent with the principles of analytical decision making."

Tushman *et al.* (2017) emphasizes that "analytics using complex data sets are playing an important role in effectively managing organizational change" and so organizational management is becoming increasingly data-driven. More recently, Duan *et al.* (2020) and Chatterjee *et al.* (2021) extensively discuss the data-driven culture evolution and organizational impact in the last decade. Their research also validates the idea that together with Business Analytics, the data-driven culture in organizations has the capability to enhance innovation, which subsequently results in higher organizational performance.

2.2 Business Intelligence and Analytics (BI&A)

Business Intelligence (BI) and Business Analytics (BA) are both well-established areas and prominent topics for IS researchers and practitioners (Chen *et al.*, 2012). BA is considered an evolution of BI, a system that offers "advanced techniques for the analysis and reporting of data" (Someh *et al.*, 2019). As reported by Brynjolfsson and McAfee (2017), BA is seen as "the next big thing" in the business community, while BA tools are expected to augment or substitute for humans in the decision-making process.

BA is adding extra functions to the BI tools that are designed for reporting, analyzing, and presenting. Davenport and Harris (2007) introduce BA the as "representing the extensive use of data, statistical and quantitative analysis, exploratory and predictive models, and fact-based management to drive decisions and actions". Business Analytics has four objectives (Yin & Fernandez, 2020). First of all, BA reduces the time spent with decision-making, thus optimizing decision-making processes in real time (Sharma *et al.*, 2014; Hindle & Vidgen, 2018). At the same time, BA increases the objectivity of decisions. As revealed in previous research, the use of BA has a positive influence on customer marketing (Schläfke *et al.*, 2012) and quality of services and product is improved (Troilo *et al.*, 2016). Last but not least, the use of BA helps understand the external environment (Calof *et al.*, 2015).

Cosic *et al.* (2012) considers BA a company asset that includes "people, processes, and technologies involved in data gathering, analysis, and transformation to support managerial decisions." As Seddon *et al.* (2017) also acknowledged, BA is about using data "to make sounder, more evidence-based decision making."

Descriptive analytics provides answers to questions such as "What happened?", "Why did it happen?", but also "What is happening now?" mostly in a streaming context. Predictive analytics determines "What will happen?" and "Why will it happen?" in the future, prescriptive analytics will provide solutions to questions such as "What should I do?" and "Why should I do?". In this respect, BA is useful for companies that plan to change their business model or seek to adapt to a new business environment. Advanced data processing algorithms such as complex statistics, data mining, machine learning are used to suggest and verify changes made to products and services in order to better match customer requirements (Djerdjouri & Mehailia, 2017).

To predict the effects of a changed business model a substantial amount of high-quality data is required and that is made available in a data-driven environment. In the Big Data and AI age, BI&A evolves to "data-driven discovery and highly proactive and creative decision making" (F. Wang *et al.*, 2022) offering the company the opportunity to spawn new competitive advantage.

BI&A had received extensive attention in literature but not many papers offered empirical evidence on BI&A effectiveness and value realization for the manager. This paper explores the relationships between BI&A adoption, decision making effectiveness, and individual work performance.

2.3 Decision making based on BI&A

Decision making is an essential managerial task which is crucial because it shapes the course of a company. Traditionally, managers use to rely on their intuition, as a "form of reasoning that is based on years of experience and learning, and on facts, patterns, concepts, procedures, and abstractions stored in one's head" (Matzler *et al.*, 2007). Today they have to rely more on gathering of facts, figures, data, and evidence and replace the intuitive decision making with the fact-based decision making. Companies accumulate immense amount of data from diverse sources but to make use of it in decision making, they need to deploy data analytics solutions (Madhala *et al.*, 2021).

In order to avoid situations like data redundancy or information overload, or incomplete information that result in mediocre outcomes, managers need the right amount of data in the suitable form. This need stimulated companies to adopt BI&A systems, aiming to optimize the decision through the "pervasiveness availability of data with quality and in a timely fashion".

The decision-making process based on BI&A tools utilizes insights that are generated by the analysis of data from multiple sources. Insights give rise to "the discovery of creative options through immersion in data" (Frisk *et al.*, 2014) and support the data-driven decisions approach (Passlick *et al.*, 2020). Traditional BI reporting systems often cannot keep up with this need and self-service BI appeared as a more flexible environment for the manager's demands, accomplishing decentralized decision making across all departments. Furthermore, the dynamic business environment and the intense competition in the last decade amplified the necessity for a fast and effective decision-making process. Business Analytics came up with the promise to create value from the huge volumes of available data.

An increased number of companies tried to benefit from the BA promise and invested in related technologies and infrastructure. Nowadays, the idea of improving the decision-making process demonstrates new opportunities due to the achieved capacity of storing and analyzing data in real-time that have expanded the data analytics capabilities (Madhala *et al.*, 2021).

3. RESEARCH METHODOLOGY

3.1 Research model and hypotheses

The proposed model is based on the previous research on impact of BI&A use on decision making and organizational performance.

According to Madhala *et al.* (2021), the categories of effects of BI&A use that are analyzed in literature are "performance, innovation, strategy, and decision-making process." Business performance constitutes the mainly researched result; literature investigated the effects of BI&A adoption on organizational performance and suggested that it results in improved effectiveness (innovation of products and services, quality, or customers' satisfaction) and efficiency (B. Chae *et al.*, 2014; Battleson *et al.*, 2016; Gupta & George, 2016; Alexander & Lyytinen, 2019; Jha *et al.*, 2020). Meanwhile, other authors (Seddon *et al.*, 2017; Ghasemaghaei, 2019) assert that there is still ambiguity on the subject of the impact of adopting of BI&A on performance, so the subject can benefit from further investigation.

To the best of our knowledge, the individual work performance is an outcome that is seldom analyzed, and our research aim to contribute in this research direction. Moreover, the proposed model includes also the decision-making process effectiveness. The complete research model is pictured in Figure no. 1.

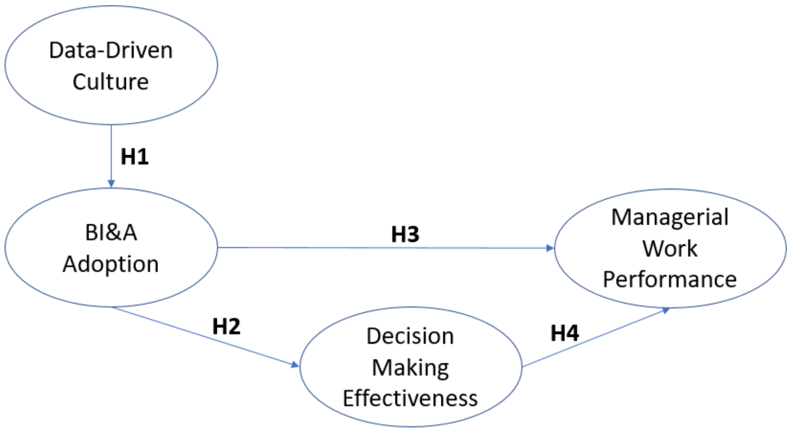

Figure no. 1 – Research Model

Our first assumption aims for determining the correlation between data-driven culture and BI&A adoption. Given the enormous volume of data created and made available to the companies, it is important for them to transform their organizational culture into a data-driven one. While other researchers consider that BA adoption determines a data-driven culture

(Chatterjee *et al.*, 2021), our intention is to test if BI&A adoption is positively influenced by a data-driven culture.

Kiron *et al.* (2013) suggested that companies need to develop "data-oriented management systems" as a proper response to the increasing volumes of data. As explained in Chatterjee *et al.* (2021), data-driven culture boosted after 2016, along with the incredible growing of connected devices and innovative data technology. In their research about the challenges tackled by managers striving for their organizations to become more data-driven with the aim of creating value, Vidgen *et al.* (2017) also enumerated "building a corporate data culture" among other data-related assignments like, "managing data quality" or "building data skills." Many organizations today recognize data as a new class of business assets and this postulation is also reflected in their investments in specific technology, like BI&A. As stated in Tavera Romero *et al.* (2021), to accomplish the BI potential, a change in culture is necessary. In the same vein, Duan *et al.* (2020) emphasized the importance of not regarding BA as "just a technical development", but also considering it strongly related to the organizational culture. In this respect, Wedel and Kannan (2016) asserted that a data-driven culture encourages BA adoption and determines the maximization of the BA potential.

Taking into consideration the fact that data and BI&A solutions increasingly become user-friendly and cost-efficient, we reason that a data-driven culture is encouraging for BI&A adoption in the organization and we articulate the first hypothesis:

***H1**: Data-driven culture is positively related to BI&A adoption.*

In 2004, (Gibson *et al.*) asserted that BI delivers substantial business value by enhancing the effectiveness of the decision-making process, being the "principal provider of decision support". Decision making effectiveness is also considered an important indicator of the BI system success (Y. Wang & Byrd, 2017).

Having in mind the differentiation between dependence and infusion of a system's use described by Sundaram *et al.* (2007), in case of the BI&A systems we don't observe the system-dependence because the manager's decision does not necessarily depend on the BI&A system use – many managers still base their decisions on intuition or 'gut'. Based on Sundaram *et al.* (2007), Trieu *et al.* (2018) explained the 'BI infusion', which happens when managers fully use the BI system for enhancing their work performance. In addition, the importance of data for the management environment is unanimously recognized, data-driven decisions are leading to beneficial actions for the organization (Sharma *et al.*, 2014; Hindle & Vidgen, 2018). BI&A is expected to deliver "the right decision support to the right people and digital processes at the right time" (Laursen & Thorlund, 2010). Basing their decisions on BI use, managers may be able to replace intuitive decision making with "fact-based decision making" (Davenport, 2006). Recent studies examined the effects of BI&A adoption on decision making. For example, Ghasemaghaei *et al.* (2018) determined that Business Analytics capabilities can significantly improve the decision-making quality. Kitchens *et al.* (2018) and Tan *et al.* (2016) discovered the BI&A contribution for optimizing decision making in the e-commerce domain.

In this vein, we posit that BI&A adoption enhances the manager's decision-making effectiveness and formulate as follows:

***H2**: BI&A adoption is positively related to decision making effectiveness.*

Complex business models and processes require a series of innovative approaches to increase managerial performance. Exploiting the full potential of internal and external data by using BI&A tools leads to increased efficiency of operations and business performance (Oliveira *et al.*, 2012; B. K. Chae & Olson, 2013).

Many papers in BI&A literature as well as business reports validated the theory that BI&A solutions are beneficial for companies because they contribute to their performance (Anderson-Lehman & Watson, 2004; Davenport & Harris, 2007; Davenport *et al.*, 2010; Shanks & Bekmamedova, 2012; Wixom *et al.*, 2013; Someh *et al.*, 2019). According to Shanks and Bekmamedova (2012), Business Analytics "provides value to the organization when it is embedded in it." As regards individual work performance, based on the frequency and duration of the IS usage, Hou (2012) discovered that "higher levels of BI system usage lead to higher levels of individual performance." It is reasonable to assume that BI&A use helps managers to accomplish their tasks more effectively and enhanced their work performance and we articulate the next hypothesis:

***H3**: BI&A adoption is positively related to managerial work performance.*

According to Sharma *et al.* (2014), the 'first-order effects' of BI&A adoption are likely to affect the decision-making process and consequently, the improved decision-making process will positively influence the organizational performance. In the same line of thought, Trkman *et al.* (2010) explained that analytical tools enhance the decision-making process and as a result the business performance increases. Data-driven decision-making has a positive effect on firm performance, in other words, companies that rely on data and facts for decision-making enhance their productivity (Brynjolfsson & McAfee, 2017).

"Make decision quicker", "Shorten the time frame for decision making", or "Spend less time in meetings" are listed as benefits of computer-aided decision making (Leidner & Elam, 1993) and it is only reasonable to assume that an effective decision-making process has a positive impact on managerial work performance. Therefore, we hypothesize:

***H4**: Decision making effectiveness is positively related to managerial work performance.*

3.2 Research Methods

Starting from these research questions, we developed a research model with four variables: Data-Driven Culture (DDC), Business Intelligence & Analytics adoption (BIAA), Decision Making Effectiveness (DME) and Managerial Work Performance (MWP). Measurement items have been already identified in previous studies: Sanders and Courtney (1985); Leidner and Elam (1993); Koopmans *et al.* (2012); Cao and Duan (2014); Chatterjee *et al.* (2021). All the items will be measured on a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree).

A pilot test will be conducted in a local IT company involving at least 10 managers at different levels and departments. The population will be selected from 40 medium and large size companies from at least four national development regions, the questionnaire being distributed to at least 10 managers from each organization. Firm size and industry (for the company), as well as managerial position and department (for the manager) will be taken as control variables.

Data will be analyzed with PLS-PM that provides the opportunity to assess the measurement of the constructs and test hypotheses on all the relationships among the constructs at the same time, in the same analysis. According to Benitez *et al.* (2020), Partial Least Squares path modeling (PLS-PM) has been "the predominant estimator for structural equation models" in the IS area.

We will test the adequacy of the model proposed regarding the reliability of data, convergent and discriminant validity. In order to validate the proposed model, further processing is necessary, and the following steps are required:

- key parameters estimation, namely the path coefficients and R2 value of the IWM latent endogenous variable (Individual Work Performance construct); the path coefficients express how strong is the effect of one variable on another variable;
- reliability and validity measurement, being essential to determine if the latent variables are reliable and valid of and the correlations among the latent constructs (DDC, BIAA, DME, IWM);
- measurement of the structural model; typical assessment standards consist of collinearity test, the coefficient of determination, the predictive relevance, and "the statistical significance and relevance of path coefficients" (Fricker *et al.*, 2012).

4. EXPECTED CONTRIBUTION

The proposed research is assumed to generate some theoretical and practical contributions. First, the research will contribute to fill the gap in the literature by investigating the relationship between BI&A adoption and decision making effectiveness and the individual work performance.

Next, our research model theorize that data-driven culture has a major positive effect on BI&A adoption because we are observing a strong belief that Big Data triggers an inevitable change in the organizational culture that is more than simply investing in the company's analytics capacity.

Third, we expect to discover differences in the adoption of BI&A tools between different managerial levels and departments and in relation to the company size and industry. These dissimilarities promise to reveal significant insights that may be useful for the BI&A adoption strategy.

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