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FACULTY OF ECONOMICS AND ADMINISTRATION

The Business Value of Business Intelligence & Analytics (BI&A)

Habilitation Thesis

AHAD ZARERAVASAN

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Author: Ahad Zareravasan
Faculty of Economics and Administration
Masaryk University

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Abstract

Business Intelligence and analytics (BI&A) has become an increasingly important research and practice topic with the emergence and availability of big data and advances in data analytics tools and techniques. In light of this, for the last seven years, I have been working on how business value can be created from Information Systems (ISs) in general and BI&A in particular. This habilitation thesis aims to summarize a collection of my eight published journal papers that appeared in peer-reviewed journals such as the International Journal of Information Management, Journal of Information science, Journal of Enterprise Information Management, and Journal of Business and Industrial Marketing. A detailed commentary has also been presented illustrating the research concerns addressed and the limitations each research faced in delivering the intended outcomes. To keep the big picture and show how published papers are related to each other, a BI&A business value framework is utilized, and each paper is mapped to the related process in the framework. Accordingly, two papers are related to the "BI&A conversion process", one paper is related to the "BI&A use process", and five papers are associated with the "BI&A competitive process". My contribution to each paper is also provided for each publication ranging from 30% to 100%, with an average of 52%. I have been the main author in five publications. All eight collected papers in this thesis received 136, 174, and 360 citations (self-citations included) from WoS, Scopus, and Google Scholar indexed journal and conference papers. The 124 citing articles to any of the collected papers in this thesis mostly belong to the "Management" and "Business" categories (of WoS).

Declaration

I certify that I have written the habilitation report "The Business Value of Business Intelligence & Analytics (BI&A)" in the form of a paper collection by myself and I have listed all the co-authors of papers and honestly filled in my contribution to each paper.

Brno, 20.01.2022

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Ahad Zareravasan

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I would like to express my appreciation to all the mentors I have had along my journey, to Dr. Payam Hanafizadeh for guiding me during my M.Sc. and Ph.D. studies, to Dr. Petr Suchánek, Dr. Ondřej Částek, and Dr. Michal Krčál for welcoming and integrating me to ESF MUNI, to Dr. Jakub Procházka, Dr. Rostislav Stanek, and Mgr. Pavel Sedláček to their seamless support in my habilitation process, and all my great team of co-authors of the collected papers specially Dr. Peter Trkman, Dr. Saeed Rouhani, Dr. Taha Mansouri, and Amir Ashrafi. Finally and foremost, I wish to thank my family and close friends for their support, understanding, and patience.

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List of Terms and Abbreviations

Abbreviations	Term
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ANP	Analytic Network Process
BA	Business Analytics
BDA	Big Data Analytics
BI	Business Intelligence
BI&A	Business Intelligence & Analytics
CEO	Chief Executive Officer
CIO	Chief Information Officer
CSFs	Critical Success Factors
DC	Dynamic Capability
DSS	Decision Support System
EFA	Exploratory Factor Analysis
FANP	Fuzzy Analytic Network Process
IoT	Internet of Things
MCDM	Multi-Criteria Decision-Making
MO	Market orientation
OLAP	On-Line Analysis Processing
OR	Operations Research
PLS	Partial Least Squares
SEM	Structural Equation Modeling
TOE	Technology, Organization, and Environment
TPS	Transactional Processing Systems
VBA	Visual Basic

1 Introduction

The increasing amount of data from different sources leads us to think more deeply about the prominent role of Business Intelligence & Analytics (BI&A). It refers to "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make a timely business decision" (Chen, Chiang, & Storey, 2012, p. 1166). BI&A as an enabler allows firms to be agile in sensing market movements, making better decisions, and acting appropriately through (1) integrating structured and unstructured data, and (2) making quality information available (Ashrafi, Zare Ravasan, Trkman, & Afshari, 2019; Teo, Nishant, & Koh, 2016). In regards, investment in the BI&A is listed on top of expense-worthy tools and applications for firms and managers, so many firms believe that not using BI&A equals losing the competitive market (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019). That is why BI&A is a topic of growing interest in both industry and academia (S. Wang, Yeoh, Richards, Wong, & Chang, 2019).

Past research unanimously confirmed the decisive role of BI&A on value creation, considering different perspectives (e.g., Fink, Yogev, & Even, 2017; Grover, Chiang, Liang, & Zhang, 2018; Seddon, Constantinidis, Tamm, & Dod, 2017), however, there is an unexplored aspect of how firms should adopt and employ complicated and costly BI&A to fully realize the promised business value (Akter et al., 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2019). While the goal of BI&A has been to facilitate decision-making, increase revenue and competitiveness, it can impose high costs for given enterprises. Hence, it indicates that adopting these systems should also be considered with caution by organizations from different aspects. In addition, inconsistency and inappropriate assessment of influencing factors during the adoption process can lead projects into failure. Thus, it is necessary to empirically investigate BI&A adoption process and, more specifically, the mechanisms in which BI&A yields business value (Abbasi, Sarker, & Chiang, 2016a; Ashrafi et al., 2019;

Günther, Mehrizi, Huysman, & Feldberg, 2017) so that firms could gain the intended business value out of their BI&A investments. The current thesis describes the applicant's efforts in addressing this research concern, i.e., getting business value from BI&A.

1.1 Goals and Structure of the Thesis

This thesis summarizes my contributions to the field of the business value of Business Intelligence and Analytics. The second chapter starts with a brief overview of the definitions of BI&A., followed by a BI&A business value framework. It gives an overall picture of the current body of knowledge and key research streams. Besides, it builds a ground to position my contributed papers in the available research topics. Chapter 3 describes each paper, including the main contributions, theoretical basis, research method, and my contribution to the paper. Finally, Chapter 4 concludes the thesis.

1.2 Paper Collection

Even though I have a good publication record on computational and algorithmic subjects of Artificial Intelligence (AI), which is relevant to the Computer Science aspects of BI&A, I only include papers in this thesis that are highly associated with the business and managerial aspects of BI&A, as it is my main research interest.

Accordingly, I have selected eight papers within the thesis domain. All of them are journal papers, with five already indexed in WoS and the other three listed only with Scopus. The list of the papers is as follows[1]:

[1] The list is ordered based on the "processes" of BI&A business value (Trieu, 2017) introduced in chapter 2, so that the first two papers are associated with the first process in the framework, third paper with the second process, and next are related to the third process.

1. Rouhani, S., & **Zare Ravasan, A**. (2015). *A Practical Framework for Assessing Business Intelligence Competencies of Enterprise Systems Using Fuzzy ANP Approach*. International Journal of Applied Decision Sciences (IJADS). 8 (1), 52-82.
2. Rouhani, S. & **Zare Ravasan, A**. (2015). *Multi-objective Model for Intelligence Evaluation and Selection of Enterprise Systems*. International Journal of Business Information Systems (IJBIS). 20 (4). 397-426.
3. **Zare Ravasan, A.**, & Rabiee Savoji, S. (2014). *An investigation of BI Implementation Critical Success Factors in Iranian Context.* International Journal of Business Intelligence Research (IJBIR). 5(3), 41-57[2].
4. Rouhani, S., Ashrafi, A., **Zare Ravasan, A.**, & Afshari, S. (2016). *The Impact Model of Business Intelligence on Decision Support and Organizational Benefits*. Journal of Enterprise Information Management. 29 (1). 19-50.
5. Rouhani, S., Ashrafi, A., **Zare Ravasan, A.,** & Afshari, S. (2017). *Business Intelligence Systems Adoption Model: An empirical investigation.* Journal of Organizational and End User Computing (JOEUC). 30(2), 43-70.
6. Ashrafi, A., & **Zare Ravasan, A**. (2018). *How market orientation contributes to innovation and market performance.* Journal of Business and Industrial Marketing. 33 (7). 970-983.
7. Ashrafi, A., **Zare Ravasan, A.,** Trkman, P., & Afshari, S. (2019). *The role of business analytics capabilities in bolstering firms' agility and performance.* International Journal of Information Management. 47. 1-15.

[2] An updated version of this paper is published later as a chapter book (citation: **Zare Ravasan, A.,** & Savoji, S. R. (2019). Business Intelligence Implementation Critical Success Factors. In *Applying Business Intelligence Initiatives in Healthcare and Organizational Settings* (pp. 112-129). IGI Global.)

8. **ZareRavasan, A.** (2021). B*oosting Innovation Performance through Big Data Analytics: An Empirical Investigation on the Role of Firm Agility*. Journal of Information Science. 01655515211047425.[3]

Further details of published papers are presented in Table 1. It includes rankings of WoS and Scopus[4], plus citation information from WoS, Scopus, and Google Scholar. According to the table, all collected papers received 136, 174, and 360 citations (self-citations included) from WoS, Scopus, and Google Scholar indexed publications. An analysis of the 136 citing articles (to any of the collected papers) in Figure 1 shows that my collected papers in this thesis received the most attention (citations) from journals with "Management" and "Business" categories (of WoS).

Additional information on how these papers are connected to the thesis domain is provided in chapters 2 and 3 of this thesis.

[3] Earlier version of this paper has been presented and received the best paper award at ICBIM 2019 (citation: **ZareRavasan, A.,** & Ashrafi, A. (2019, September). An empirical investigation on big data analytics (BDA) and innovation performance. *In Proceedings of the 3rd International Conference on Business and Information Management*. Paris. France. pp. 97-101.

[4] AIS and IFs refer to Clarivate data on the published year. Scimagojr ranking data for the published year is used for Scopus indexed journal papers. In case of multiple quarters for a journal, the best or most relevant quarter is mentioned. Citation counts are conducted on December 2021.

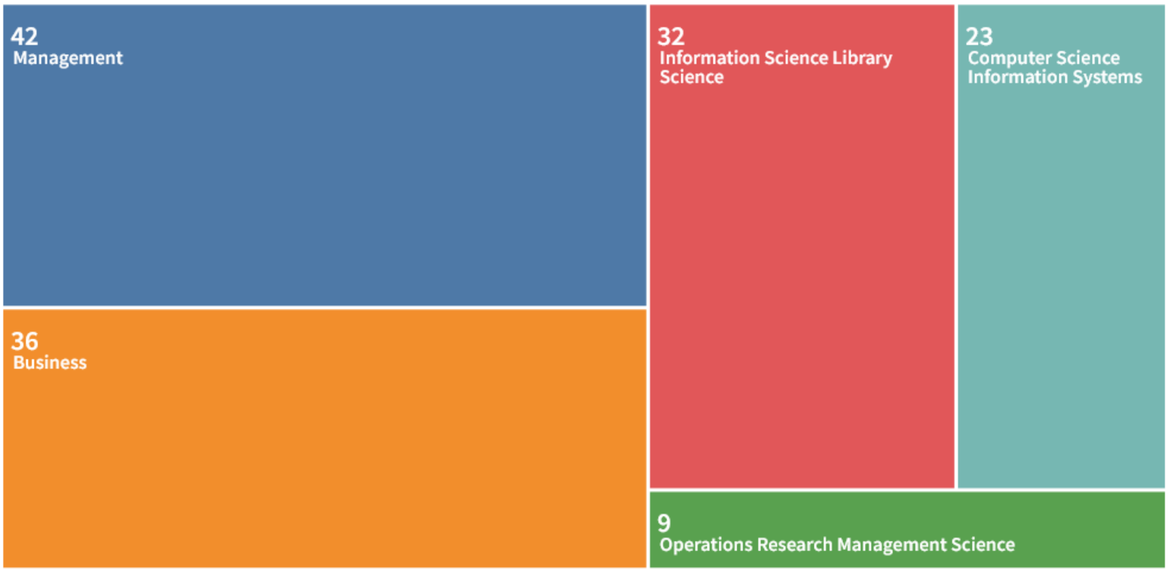

Figure 1. WoS categories of citing articles to the collected papers (Source: WoS)

Table 1. Published papers and the ranking of journals

Id	Journal title	Publisher (year)	My contribution	WoS AIS Quartile	WoS IF Quartile (IF)	Scopus Quartile	Citations		
							WoS	Scopus	Scholar
Paper#1	International Journal of Applied Decision Sciences	Inderscience (2015)	50%	-	-	Q2 (Strategy & Management), Q2 (Information Systems and Management).	-	5	8
Paper#2	International Journal of Business Information Systems	Inderscience (2015)	50%	-	-	Q3 (Information Systems and Management), Q3 (Management of Technology and Innovation).	-	3	6
Paper#3	International Journal of Business Intelligence Research	IGI-Global (2014)	75%	-	-	Listed from 2019 Q4 (Information Systems and Management), based on 2020 data.	-	-	25
Paper#4	Journal of Enterprise Information Management	Emerald (2016)	30%	Listed from 2017. Q3 (Information Science & Library Science), based on 2020 data.	Listed from 2017. Q1 (5.396), based on 2020 data.	Q1 (Library and Information Sciences), Q1 (Information Systems), Q2 (Management of Technology and Innovation).	23	37	112
Paper#5	Journal of Organizational and End User Computing	IGI-Global (2017)	30%	Q3 (Information Science & Library Science), Q4 (Computer Science, Information Systems), Q4 (Management).	Q3 (0.744).	Q2 (Strategy and Management).	11	11	27
Paper#6	Journal of Business and Industrial Marketing	Emerald (2018)	50%	Q3 (Business).	Q3 (1.961).	Q1 (Business and International Management).	28	29	46
Paper#7	International Journal of Information Management	Elsevier (2019)	30%	Q1 (Information science & Library Science).	Q1 (8.210).	Q1 (Information Systems), Q1 (Information Systems and Management).	73	88	135
Paper#8	Journal of Information Science[5]	Sage (2021)	100%	Q3 (Computer Science, Information Systems), Q3 (Information Science & Library Science).	Q2 (3.282).	Q1 (Information System), Q1 (Library and Information Sciences).	1	1	1
Sum							**136**	**174**	**360**

[5] AIS and IF data of 2020 is used for Paper#8.

2 BI&A and business value

This chapter presents a short overview of the BI&A concept and then presents a BI&A business value framework that is adopted in this thesis to posit the collected papers and illustrates how they are connected to BI&A business value.

2.1 Business Intelligence and Analytics (BI&A)

Business Intelligence and analytics (BI&A) has become an increasingly important research and practice topic during the last years (Agarwal & Dhar, 2014). Rather than having a generally-accepted and specific definition, BI&A is typically used as an 'umbrella' term to describe a process (Shollo & Kautz, 2010), or concepts and methods (Sabherwal & Becerra-Fernandez, 2013), that improve decision making by using fact-based support systems. Many terms (such as "business intelligence", "business analytics", "big data", "data mining", and "data warehousing") are often used interchangeably in the literature, with authors variously describing BI as a "process and a product" (Jourdan, Rainer, & Marshall, 2008, p. 121), "a process, a product, and a set of technologies, or a combination of these" (Shollo & Kautz, 2010, p. 87), or a product alone (Seddon et al., 2017). However, the first scientific definition, by Ghoshal and Kim (1986), referred to BI&A as a management philosophy and tool that can help organizations manage and refine business information systems to make effective decisions. It can be viewed as the intersection of a variety of disciplines, of which Operations Research (OR), Artificial Intelligence (AI), and information systems (ISs) are of particular relevance (Hindle, Kunc, Mortensen, Oztekin, & Vidgen, 2020)(see Figure 2).

BI&A is considered an analysis instrument, providing automated decision-making about business conditions, sales, customer demand, and product preference. It uses large database (data-warehouse) analyses, as well as mathematical, statistical, and artificial intelligence, data mining, and On-Line Analysis Processing (OLAP) (Berson & Smith, 1997).

Eckerson (2010) stated that BI&A must be able to provide the following tools: production reporting tools, end-user query and reporting tools, OLAP, dashboard/screen tools, data mining tools, and planning and modeling tools. Also, according to Tutunea & Rus (2012), the BI&A solutions/products, have modular functionalities that include dashboards, localization, and business data visualization in geographical or geo-location format, what-if analysis, interactive reports, and finally sharing, distributing information to users, viewable in normal, easily interpretable format.

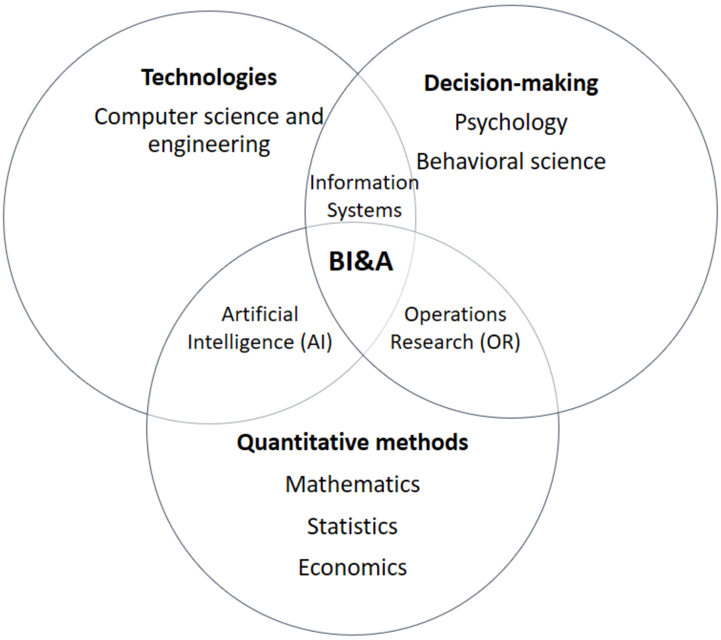

Figure 2. BI&A disciplines (Hindle et al., 2020)

A literature review of BI&A reveals a division between technical and managerial viewpoints, following two broad patterns. The managerial approach sees BI&A as a process in which data are gathered from inside and outside the enterprise and are integrated to generate information relevant to the decision-making process. From this viewpoint, the role of BI&A is to create an informational environment in which operational data gathered from Transactional Processing Systems (TPS) and external sources can be analyzed to extract strategic business knowledge to support the unstructured decisions of management. The technical approach considers BI&A as a set of tools that supports the process described above. The focus is not on the process itself but on the technologies, algorithms, and tools that allow the saving, recovery, manipulation, and analysis of data and information (Petrini & Pozzebon, 2008).

However, in the overall view, there are two important issues. First, the core of BI&A is the gathering, analysis, and distribution of information. Second, the objective of BI&A is to support the strategic decision-making process. Strategic decisions are decisions related to implementation and evaluation of organizational vision, mission, goals and objectives, which are supposed to have medium to long-term impact on the organization, as opposed to operational decisions, which are day-to-day in nature and more related to execution (Petrini & Pozzebon, 2008). Bose (2009) also describes the managerial view of BI&A as a process to get the right information to the right people at the right time so they can make decisions that ultimately improve the performance of the enterprise.

The technical view of BI&A usually centers on the processes, applications and technologies for gathering, storing and analyzing data, and for providing access to data that helps management make better business decisions. Another important observation in the BI&A evolution is that industry leaders are currently transitioning from the operational BI&A of the past to the analytical BI&A of the future, which focuses on customers, resources, and capabilities to influence new decisions every day. They have implemented one or more advanced analytics forms to meet these business needs. Ranjan (2008) considers BI&A as the conscious, methodical transformation of data from any data source into new forms to provide business-driven and results-oriented information. It will often encompass a mixture of tools, databases, and vendors to deliver an infrastructure that will deliver the initial solution and incorporate the capability to change with the business and the current marketplace.

Wu et al. (2007) define BI&A as a business management term used to describe applications and technologies that are used to gather, provide access to, and analyze data and information about the organization to help management make better business decisions. In other words, the purpose of BI&A is to provide actionable BI&A technologies including traditional data warehousing technologies, such as reporting, ad hoc querying, and OLAP.

Elbashir et al. (2008) refer to BI&A as an important group of systems for data analysis and reporting that support managers at different levels of the organization with timely, relevant, and trouble-free ways to use information, enabling them to make better decisions. They explain that BI&A systems are often implemented as enhancements to widely adopted enterprise systems, such as ERP systems. The scale of investment in BI&A systems is reflected in their growing strategic importance, highlighting the need for more attention in research studies.

Jalonen and Lonnqvist (2009) declared that BI&A generates analyses and reports on trends in the business environment and on internal organizational matters. They explained that analyses may be produced systematically and regularly, or they may be ad-hoc, related to a specific decision-making context. This knowledge is employed by decision makers at different organizational levels. This process results in the generation of both numerical and textual information. These definitions engender two important propositions:

1. Often, approaches to BI&A are limited by the supported functions, systems, or system types.

2. BI&A is aimed primarily at providing an organization’s management with decision-relevant analytic information in support of their management activities.

In Table 2, BI&A definitions are divided, based on three approaches: a managerial approach, a technical approach, and an approach to BI&A as an enabler of enterprise systems. The new perspective of system enabler by Ghazanfari et al. (2011) refers the value-added features on supporting information.

Table 2. BI&A definitions, adopted from Ghazanfari et al. (2011)

BI&A Definition	**Managerial Approach**	**Technical Approach**	**System-enabler Approach**
Focus	Excellence of management decision-making process	Tools that support the process of the managerial approach to BI	Value-added features on supporting information
References	(Bose, 2009; Ghoshal & Kim, 1986; Jalonen & Lönnqvist, 2009; Maria, 2005; Petrini & Pozzebon, 2008; Power, 2008)	(Berson & Smith, 1997; Bucher, Gericke, & Sigg, 2009; Mathew, 2012; Petrini & Pozzebon, 2008; Wu et al., 2007)	(Cates, Gill, & Zeituny, 2005; Eckerson, 2010; Elbashir et al., 2008; Lönnqvist & Pirttimäki, 2006; Ranjan, 2008)

In light of the above discussion, we adopt a balanced perspective throughout this thesis and define BI&A as:

“***A strategic*** **decision** ***aid for organizations to collect, and analyze data sources using diverse technological tools to support organizational decision making and finally increasing organizational performance*****”.**

With such a view, three categories of BI&A can be introduced as:

- Descriptive analytics: descriptive analytics mainly focuses on answering what happened in the past through a set of tools, including Key Performance Indicators (KPIs), dashboards, and descriptive statistics (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017). It is the most common and purest form of analytics that opens up new avenues for firms from exploratory insight (Phillips-Wren, Iyer, Kulkarni, & Ariyachandra, 2015).

- Predictive analytics: this type of analytics refers to the use of knowledge extracted from descriptive analytics to realize what will happen in the future. It goes through techniques such as statistical analysis, forecasting models, Natural Language Processing (NLP), text mining, and Artificial Neural Networks (ANNs) (Grover et al., 2018). It allows users to predict future possibilities and discover hidden relationships to make the most likely patterns (Phillips-Wren et al., 2015).

- Prescriptive analytics: it follows to find out what is the optimal solution based on the knowledge given from the descriptive and predictive analytics (Holsapple, Lee-Post, & Pakath, 2014). This makes value through the recruiting optimization approach, recommending solutions, and evaluating their influence regarding business consideration (Sivarajah, Kamal, Irani, & Weerakkody, 2017).

2.2 A Framework for BI&A Business Value

To provide a comprehensive end-to-end view of the processes through which business value is obtained from BI&A, a framework is required to structure the analysis. Trieu (2017), synthesizing IS business value models of Soh and Markus's (Soh & Markus, 1995), Melville et al.'s (2004), and Schryen's (2013), presents such a framework (see Figure 3). The basic idea of this framework is that the link from BI&A investments to organizational performance can be modeled as a chain of necessary conditions, such that increases in organizational performance require a necessary degree of BI&A impacts, which in turn require BI&A assets, which finally require BI&A investments. Following the logic of process models (Trieu, 2017) each link in the chain reflects a probabilistic process. For instance, the link from investments to assets involves the process of BI&A management/conversion and investment in complementary (non- BI&A) investments, the link from BI&A assets to BI&A impacts depends on the process of using BI&A effectively, and the link from BI&A impacts to organizational performance depends on the competitive process.

This framework accounts for three value generation processes (the conversion process, use process, and competitive process), as well as contextual/environmental factors, and latency effects. Overall, it suggests that BI&A business value generation involves the following set of necessary conditions and probabilistic processes: organizations invest in BI&A, and subject to the varying degrees of effectiveness during the BI&A management process and non- BI&A investments, obtain BI&A assets. Quality BI&A assets, if used effectively, then yield desired BI&A impacts, which help yield organizational performance. Contextual/environmental factors include firm (or organizational), industry, and country factors that influence the BI&A use process and the competitive process. Firm factors can also influence the BI&A use process, whereas both industry factors and country factors influence the competitive process. Latency effects need to be considered to account for organizational learning and adjustment. Trieu's (2017) review of BI&A studies yields the framework in Figure 3, in which the degree of shading reflects the amount of attention each element has received in the literature. For instance, it shows that the relationship between "BI&A Assets" and "BI&A impacts" has been addressed in over 30% of his reviewed pool of papers.

This thesis uses Trieu's (2017) framework not only to illustrate the main research streams in the field (and the focus of prior research on each, i.e., the percentiles in the bottom left side of Figure 3), but also to position the collected papers in the three categories of processes mentioned in the framework. Accordingly, Paper#1 and Paper#2 fall in the "BI&A Conversion Process". Paper#3 concerns the "BI&A Use Process", and Papers#4-8 are related to the "BI&A Competitive Process" (see Figure 3). Further explanation of the papers and how they are related to the mentioned categories are presented in the next chapter.

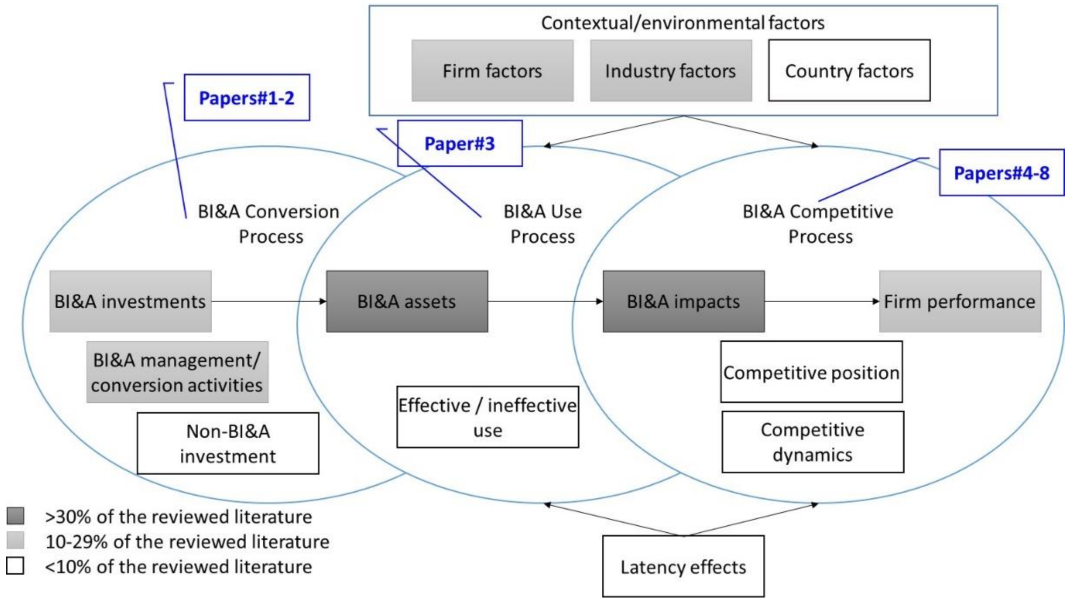

Figure 3. BI&A Business Value Framework (Trieu, 2017) and positioning of the papers

3 Summary and Scientific Contributions of the Published Papers

This chapter presents a summary of my published papers with a focus on the research gap they addressed, their contribution, and adopted research methods and approaches. Based on the three BI&A Conversion Process, BI&A Use Process, and BI&A Competitive Process of the BI&A Business Value Framework (Trieu, 2017) mentioned earlier, eight published papers are assigned to a respective process category and described below.

3.1 Papers in the “BI&A Conversion Process” category

BI&A Conversion Process addresses the process of converting BI&A investment to BI&A. Assets can be used later to create a business value (Trieu, 2017). BI&A Investment consists of investments in related hardware, software and technical infrastructure, human resources, and management capabilities (Schryen, 2013). Prior research has generally argued that BI&A Investments result in better business performance (Borrajo et al., 2010; Francalanci & Morabito, 2008; Petrini & Pozzebon, 2009; Trkman, McCormack, De Oliveira, & Ladeira, 2010). However, among many other important factors in the BI&A Conversion Process (e.g., BI&A management practices, non- BI&A investments, synergies between BI&A systems and other systems) (Trieu, 2017), choosing the right BI&A system is vital to get value. Several criteria, techniques, tools and methods for evaluating and selecting software were reviewed in the literature (Jadhav and Sonarb (2009, 2011)) for information systems selection. However, in the field of BI&A, the few efforts to evaluate the intelligence of enterprise systems have always considered BI&A as tools or systems that are separate from the other enterprise systems.

For instance, Lönnqvist and Pirttimäki (2006) designed a performance model to measure and evaluate BI&A, but their criteria were restricted to determining BI&A investment worth and BI&A values. Elbashir et al. (2008) discussed the measurement of the effects of BI&A on business processes and presented a model to make these measurements and Lin et al. (2009) have developed a performance assessment model for BI&A using Analytic Network Process (ANP). Nonetheless, these last two models also treated the BI&A as separate systems. Recently, Popovič et al. (2012), in a near domain, has evaluated the effectiveness of BI&A systems and proposed a model based on the relationships between maturity, information quality, analytical decision-making culture, and information use for decision-making as significant elements of BI&A systems success. This brief review reveals the gap and a lack of practical guidance including factors, criteria and processes to assess enterprise systems for their BI&A capabilities.

With this in mind, I have Paper#1 and Paper#2 addressing this research concern as follows. Both these papers are outcomes of a research project[1] that aimed to support an Iranian international offshore engineering and construction company in the oil industry to select and acquire an ERP system, considering the BI&A features of the system.

[1] I was a key team member in this project that has been delivered by a private consulting company.

3.1.1 Paper#1. A Practical Framework for Assessing Business Intelligence Competencies of Enterprise Systems Using Fuzzy ANP Approach

- Rouhani, S., & **Zare Ravasan, A.** (2015). *A Practical Framework for Assessing Business Intelligence Competencies of Enterprise Systems Using Fuzzy ANP Approach*. International Journal of Applied Decision Sciences (IJADS). 8 (1), 52-82.
- **Contribution (50%):** I have contributed to this paper in the problem statement, literature review, conceptual model development, and case study data collection. I was also the corresponding author of this paper.

This paper presents a practical framework for assessing the BI&A capabilities of enterprise systems based on a set of novel factors and utilizing Fuzzy Analytic Network Process (FANP) (Chang, 1992, 1996). Through this, the construct of BI competency is decomposed into three main competency parts including 'managerial', 'technical' and 'system enabler' sub-goals, five main factors ('analytical and intelligent decision-support', 'providing related experimentation and integration with environmental information', 'optimization and recommended model', 'reasoning', 'enhanced decision-making tools',) and 26 criteria. Using this framework, the BI&A competency level of enterprise systems can be determined which can help the decision-makers to select the enterprise system that best suits organizations' needs. In order to validate the proposed model, it is applied to an Iranian international offshore engineering and construction company in the oil industry to select and acquire ERP system. This research provides a complete frame (factors, criteria and procedures) for firms to assess their proposed software and systems in the field of BI&A competencies and functions.

The major contributions of this research are as follows. First, this paper, demonstrated the significance of BI&A competency assessment in enterprise systems. Second, a fuzzy ANP framework for BI&A competency assessment has been proposed with the goal of extending the current literature in the field. The framework facilitates assessing the BI&A capabilities of enterprise systems, and a corresponding fuzzy ANP architecture that supports and coordinates the work of decision-making in real problems. Third, this paper presents an application of the proposed framework to a real case. To sum up, this model provides an assessment of the BI&A requirement of an enterprise system which encompasses the nonlinear relationships among interdependent levels. The proposed model can help practitioners assess, select and acquire enterprise systems more appropriately, regarding their BI&A and decision support requirements. Additionally, using this model, the current state of BI&A capabilities or competencies of enterprise systems and possible areas of improvement can be identified in order to improve the decision-making environment of an organization.

The proposed model is a practical tool for real case problems, but using the model in other cases depends heavily on the priorities and unique requirements of the organization under study and thus is case-dependent. The weights of criteria and competency of enterprise systems fit for one case are not necessarily applicable for another one. Thus, all the expert judgments in pairwise comparisons must be changed for any new case. Therefore, caution should be exercised in generalizing the proposed model to further organizations. However, since the achieved results were heavily dependent on experts' competence and proficiency both in the subject of BI&A and business requirements, it functioned as the main limitation of the present study.

Although the case study demonstrated the model's usefulness for BI&A competency assessment, further research is needed to fine-tune the proposed model. Applying other Multi-Criteria Decision-Making (MCDM) methods in a fuzzy environment to assess enterprise systems by considering BI&A criteria and comparing the results of these methods is also recommended for future research. Furthermore, since the proposed method involves a large number of numerical computations, a user-friendly intelligent Decision Support

System (DSS) have to be developed to save time and effort in both making pairwise comparisons and interpreting the results of the fuzzy ANP. Besides, developing a group decision-making system can be very useful. In this way, the opinions of different authorities can be taken into account. Also, different hierarchical and detailed objectives can be incorporated into the study. Additionally, mathematical models or meta-heuristics can be combined with the existing method.

3.1.2 Paper#2. Multi-objective Model for Intelligence Evaluation and Selection of Enterprise Systems

- Rouhani, S. & **Zare Ravasan, A.** (2015). *Multi-objective Model for Intelligence Evaluation and Selection of Enterprise Systems*. International Journal of Business Information Systems (IJBIS). 20 (4). 397-426.
- **Contribution (50%):** I have contributed to this paper in the problem statement, literature review, conceptual model development (functional and non-functional criteria), and case study data collection. I was also the corresponding author of this paper.

Paper#2 proposes a fuzzy MCDM procedure and a multi-objective programming model to evaluate and make final decisions about the selection of enterprise systems that also include the requirements of BI&A and their other goals and requirements. To design the model, we took ideas from Sen et al. (2009) and Ziaee et al. (2006) and extended their works. In this model, six objectives that compete with each other are considered. These objectives are: maximizing the intelligence of the enterprise systems, maximizing the coverage of the functional requirements, maximizing the coverage of the non-functional requirements, maximizing the integration of the enterprise systems, minimizing implementation costs, and optimizing the required implementation time (because of parallel implementations) totally. The structure of the multi-objective model made us to combine different objectives by minimizing their deviations from goal value. Objectives are modeled in the form of limitation with an equal equation to the target value and the objective function, we should minimize their deviation, and with this role, they would be equaled with that target value. In order to validate the model with a real application, all phases of the approach were applied in the evaluation of the enterprise systems of a company in the oil industry.

There are some main contributions of the current research. At first, this paper proposed BI&A capabilities as evaluation criteria for enterprise systems. Second, it provided a new and more holistic multi-objective model to select enterprise systems considering six aspects of software quality and implementation. Third, a Pareto optimality pattern has been utilized to balance the priority of objectives to achieve the best solutions.

Although the case study is related to a specific enterprise system and industry, the same approach can be applied to other enterprise systems and different organizations. Visual Basic macros (VBA) in Microsoft Excel were developed to carry out the fuzzy calculation during the actual evaluation. Therefore, an increase in the number of requirements is not a limitation, but the main limitations of this research include the need for gathering huge data, ambiguity in the exact combination of different objectives, and the novelty of intelligence requirements in business and industry. Applying other MCDM methods in a fuzzy environment to evaluate enterprise systems and comparing these methods to develop expert systems for the selection of enterprise systems and also utilizing efficient multi-objective and Pareto techniques are recommended for future research.

3.2 Papers in the “BA Use Process” category

According to Trieu (2017), high-quality BI&A Assets are necessary but not sufficient condition, to result in BI&A Impacts, because any deficiency in system development or planning can diminish the effectiveness and result in negative impacts. Paper#3 addresses Critical Success Factors (CSFs) in the BI&A implementation that can help organizations to focus on the key areas and mitigate the risks.

3.2.1 Paper#3. An investigation of BI Implementation Critical Success Factors in Iranian Context

- **Zare Ravasan, A.**, & Rabiee Savoji, S. (2014). *An investigation of BI Implementation Critical Success Factors in Iranian Context.* International Journal of Business Intelligence Research (IJBIR). 5(3), 41-57.
- **Contribution (75%):** I have contributed to this paper in the problem statement, literature review, conceptual model development, data analysis and discussion. I was also the corresponding author of this paper.

Rasmussen, Goldy, and Solli (2002) declared that the cost of buying and implementing BI&A software could vary from 50 thousand dollars to millions. Sahay and Ranjan (2008) and Ramamurthy, Sen, and Sinha (2008) also cited the tremendous cost of BI&A implementation in the organizational environment. Then, while the goal of BI&A has been to facilitate decision-making, increase revenue and competitiveness, it can impose high costs for given enterprises. Hence, it indicates that adopting these systems should also be considered with caution by organizations from different aspects. In addition, it is evident that the occurrence of inconsistency and inappropriate assessment about influencing factors during the implementation process can lead projects into failure.

Despite its importance and aforementioned high failure rate, few studies have Investigated the success or failure critical factors in the implementation of these systems

(Jagielska, Darke, & Zagari, 2003). Therefore, empirical research is needed to shed more light on those CSFs influencing the implementation of BI&A systems. An understanding of the CSFs enables BI&A stakeholders to optimize their scarce resources and efforts by focusing on those significant factors that are most likely to aid a successful system implementation (Yeoh & Koronios, 2010). Considering the fact that the rate of BI&A systems implementation is rising in Iran and these projects, by their nature, are associated with a high failure rate, so it is of crucial importance to identify the CSFs in such projects. Therefore, this study intends to identify and classify the BI&A implementation CSFs in Iranian cases. For this purpose, through in-depth literature review, 26 CSFs are identified, and a classification model is proposed using Robust Exploratory Factor Analysis (EFA) (Treiblmaier & Filzmoser, 2010). Through this, CSFs were categorized into four main “Organizational”, “Human Resources”, “Project Management”, and “Technical” groups.

This study suffers from some limitations. This study is by no means exhaustive enough to address all issues related to BI&A success factors. It is also difficult to make generalizations based on the contents of the work done here, and relatively few articles could be found in developing countries. As a potential topic for further research, the conceptual framework could be applied to other countries to investigate its applicability. Likewise, researchers may adopt qualitative research methods such as case studies to investigate such factors in similar or different settings. Moreover, future work could focus on more specific areas such as project management, organizational structure, or organizational culture impact on BI&A implementation projects so that more detailed and in-depth information or deep-rooted failure-success reasons could be identified. Furthermore, future research can move beyond listing CSFs and exploring their interrelationships. For example, it is worthwhile to investigate whether mismatches between factors such as management, processes, human resources, structures, and technology are the causes of these problems. It would also be valuable to relate CSFs to project phases.

3.3 Papers in the "BA Competitive Process" category

BI&A impacts are important and necessary but not sufficient to result in improved organizational performance if business conditions are not favorable. Based on the BI&A value model (Trieu, 2017), the necessary conditions and probabilistic factors that these models suggest are critical for BI&A impacts to improve organizational performance include the competitive position of an organization, competitive dynamics, industry, and country factors, and latency effects. The main focus of my published papers are dedicated to addressing this research stream as specified below.

3.3.1 Paper#4. The impact model of business intelligence on decision support and organizational benefits

- Rouhani, S., Ashrafi, A., **Zare Ravasan, A.**, & Afshari, S. (2016). *The Impact Model of Business Intelligence on Decision Support and Organizational Benefits*. Journal of Enterprise Information Management. 29 (1). 19-50.
- **Contribution (30%):** I have contributed to this paper in the problem statement, conceptual model development, and data analysis.

BI&A is considered to equip decision-makers with required information in both tactical and strategic levels for understanding, managing, and coordinating the operations and processes in organizations (Tseng & Chou, 2006). In the simplest sense, all these capabilities seek to provide users with acceptable assistance in the decision-making process. By the same token, various benefits of organizational decision support have emerged in the academic literature (Bucher et al., 2009; Moss & Atre, 2003; Turban, Sharda, Aronson, & King, 2008; Vercellis, 2009). According to the goal of BA&I, which covers decision support in all organizational levels, the understanding of what benefits of decision support concept are driven by what functions of BI&A and also determining which function has more effect on decision support benefits and consequently organizational benefits is still unclear.

Hence, in this study, we examined the effect of each capability or function of BI&A on various dimensions of decision support benefits in a conceptual model. The proposed model provides new insight into the relation between BI&A functions, decision support benefits, and organizational benefits. This paper seeks to address the following research questions:

- What is the relationship between different BI&A functions and decision support benefits?
- What is the relationship between different decision support benefits and organizational benefits?

To address the raised research questions, the Partial Least Squares (PLS) technique is employed using a sample of 228 firms from different industries located in Middle-east countries. The findings confirm the existence of meaningful relationship between BI&A functions, decision support benefits, and organizational benefits. This study makes the following contributions:

- It offers a comprehensive model incorporating a coherent set of BI&A functions, decision support benefits, and organizational benefits that are validated.
- It provides an insightful understanding for enterprises to the forefront of the importance of analytical and intelligent decision support, and reasoning function in the way of decision-making process.
- Although the main objective of this study is so clear, there is no prior validated conceptual model.
- In this study, we assumed the decision support concept as a mediating vein to correlate BI&A functions to organizational benefits to find both significant and non-significant relationships between them.

This study has five main limitations. First, we focused on a limited number of benefits in terms of the decision support environment. Although these are known as the most famous benefits, other benefits such as greater reliability, better communication, and coordination could also be considered. Second, this research does not have a strong theoretical background in some parts of the relationships between BI&A function and decision support benefits. Although the proposed hypotheses were established through logical reasoning on BI&A function associated with decision-support benefits, we did not provide certain robust theoretical background for the model in mentioned parts. Third, there are several different approaches to describe BI&A, which unconsciously affect and create bias on participants' responses here. We tried to minimize this bias by giving the questionnaire a standard and spectrum definition of BI&A. Forth, while making generalizations from the research sample, the context of the Middle East has to be considered. It is impossible to establish the validity of findings based on a single study. Further testing of the proposed model should seek to establish its validity in other contexts. Finally, research limitation is the choice not to use control variables, such as industry type, organization size, or management support, that could influence the dependent variables. We did not include these additional control variables in the model because of the relatively small sample size. Based on mentioned limitations and considering the results obtained in the study, it is possible to make some insightful recommendations for future research. First, it is impossible to establish the validity of findings based on a single study. Further testing of the proposed model should seek to establish its validity in other contexts. Second, using a broad span of benefits in decision support and organizational context might present more valuable knowledge for organizations. Finally, it is recommended to consider the aforementioned control variables on the model behavior and map the relationships based on the decision environment.

3.3.2 Paper#5. Business Intelligence Systems Adoption Model: An Empirical Investigation

- Rouhani, S., Ashrafi, A., **Zare Ravasan, A.,** & Afshari, S. (2017). *Business Intelligence Systems Adoption Model: An empirical investigation.* Journal of Organizational and End User Computing (JOEUC). 30(2), 43-70.
- **Contribution (30%):** I have contributed to this paper in the problem statement, conceptual model development, and data analysis.

Despite all the benefits of BI&A, it should be noticed that BI&A implementation may impose significant costs (Rasmussen et al., 2002). Thus, given the remarkable costs, it is better for organizations to focus on a different aspect of this issue, and consider influential factors associated with the adoption process (Ravasan & Savoji, 2014). Previously, several studies have been conducted to explore different factors which may affect the information systems adoption decision. However, relatively few attempts have been conducted to determine the influencing factors associated with adopting BI&A systems. Thus, in considering the rapid increase in the amount of data throughout the organization and also concerning the importance of managerial decision making, it is evident that determining the most relevant factors in terms of BI&A adoption have a profound impact on the decision to employ it (Hou, 2013, 2014). Further, it will be necessary for organizations as a strategic, broad map to take the proper action in the way of BI&A adoption. Thus, the main objective of this study is to examine the adoption factors which affect BI&A implementations. Specifically, the paper seeks to address the following research questions.

- RQ1. What are the key tailored factors related to the adoption of BI&A systems regarding Technology, Organization, and Environment (TOE) framework?

- RQ2. What are the major differences between adopters and non-adopters groups in the relationship with BI&A adoptive construct?

In response to the above research questions, this study attempts to identify the critical factors influencing the adoption of BI&A through survey data. Finally, there are several important contributions to IT adoption literature as follows:

- It offers a model incorporating a set of technological, organizational, and environmental factors in BI&A adoption that is validated using PLS.

- It provides an insightful understanding for enterprises to the forefront importance of perceived tangible and intangible benefits in BI&A adoption.

PLS was used for data analysis and testing the relevant hypotheses. The results of this article show that perceived tangible and intangible benefits, firm size, organizational readiness, strategy, industry competition and competitors' absorptive capacity affect BI&A adoption.

There are several limitations to this study. First, the research model and hypotheses were developed based on the TOE framework. For future research, adoption decisions could be examined by other theoretical perspectives such as an institutional theory or expanding the TOE framework by adding more dimensions (e.g., Gu, Cao, & Duan, 2012). Second, we restricted ourselves to sampling from the financial industry. It means that we are not confident that achieving results is similar to other industries. Hence, we suggest that to generalize the results of this study, it must be exercised in an overall lens by validating within different industries. Third, the results of this study reflect the Iranian perspective. Put simply, cultural differences may significantly influence and create different results. Hence, it is recommended for future research to focus on cultural issues besides the other aspects of BI&A adoption.

3.3.3 Paper#6. How market orientation contributes to innovation and market performance

- Ashrafi, A., & **Zare Ravasan, A**. (2018). *How market orientation contributes to innovation and market performance.* Journal of Business and Industrial Marketing. 33 (7). 970-983.
- **Contribution (50%):** I have contributed to this paper in the literature review, conceptual model development, data analysis and discussion. I was also the corresponding author of this paper.

Within the past decade, firms have competed to attract customers' attention and attempted to generate superior value regarding market changes (customer preferences or competitors' action) (Terawatanavong, Whitwell, Widing, & O'Cass, 2011). Market orientation (MO) has therefore become an invaluable approach to achieve market-related information (i.e., customers' needs), offer effective responses (Tippins & Sohi, 2003), and highlight the role of innovation as a crucial concept in creating competitive advantage through developing unique products or services (Bellamy, Ghosh, & Hora, 2014). Yet, the understanding of the different perspectives of MO and how it affects innovation and market performance need further studies. Thus, the present study intends to determine the influence of MO on innovation and market performance by considering MO from the market intelligence perspective.

Regarding market intelligence perspective, MO refers to "the extent in which a firm engages in generation, dissemination, and respond to market intelligence of current and future customer's needs, competitor's strategies and actions, channel requirements and abilities, and the broader business environment" (Morgan, Vorhies, & Mason, 2009, p. 910). Put simply, it refers to the generation of market intelligence based on both current and potential customers (intelligence generation), dissemination of intelligence within and across business units (intelligence dissemination), and responding to the market (responsiveness).

Previous scholars have extensively addressed the impact of MO on diverse areas such as relational capabilities (Smirnova, Naudé, Henneberg, Mouzas, & Kouchtch, 2011), innovation speed (Carbonell & Rodríguez Escudero, 2010), and firm's performance (Han, Kim, & Srivastava, 1998; Morgan et al., 2009) among others. Despite the significant progress in innovation performance field (Dekoulou, Dekoulou, Trivellas, & Trivellas, 2017; Grinstein, 2008; Yi Wang et al., 2013), there are some inconsistencies in the way MO influences innovation performance (Song, Wei, & Wang, 2015). Besides, few attempts have been undertaken to expose factors that moderate the link between MO and innovation performance (Song et al., 2015). To address this research gap, this research examines the moderating role of flexible IT infrastructure, which is a technological foundation planned and developed over time (Ray, Muhanna, & Barney, 2005). It also considers the moderating role of BI&A as a firm's capability to analyze the obtained data and support decision-making processes in response to market needs (Asadi Someh & Shanks, 2015; Popovič et al., 2012; Popovič, Hackney, Coelho, & Jaklič, 2014). This paper also uses market turbulence as an external moderator influencing the relationships among MO, innovation and market performance. Specifically, the paper seeks to address the following research questions:

- RQ1. How does MO perspective contribute to innovation and market performance?
- RQ2. How does flexible IT infrastructure moderates the link between intelligence generation and dissemination?
- RQ3. How does BI&A capability moderates the link between intelligence dissemination and responsiveness?
- RQ4- How does market turbulence influence the link among responsiveness, innovation and market performance?

To address these research questions, a questionnaire-based survey was undertaken to test the proposed hypotheses. To verify the proposed theoretical model, we performed PLS with 114 valid survey data from different Iranian industries.

The main contribution of this paper is to investigate the roles of flexible IT infrastructure, BI&A capabilities, and market turbulence as the potential moderators in the proposed model. The results advance the understanding of the influence of BI&A capabilities on the link between intelligence dissemination and responsiveness. Findings also show innovation performance as a remarkable and valuable capability, leading to higher performance in marketing-related activities, particularly in highly turbulent markets.

Nevertheless, the present study encountered four main limitations. First, this research suffered from the cross-sectional approach (using a questionnaire-based survey at a single point in time); thus, we could not understand dynamics among respondents' perceptions. Future research should dwell on longitudinal perspectives to fully understand the dynamics of the constructs over time. Second, we researched Iran as a developing country context, and the findings just reflect the Iranian perspective. Subsequent studies could focus on other contexts, whether developing or developed countries, and compare the results with this study. Third, we ignored the role of firms' absorptive capacity and its impact on responsiveness and innovation performance. Future research could highlight the importance of absorptive capacity within the firm and examine how this issue impacts both innovative capability and firm agility. Lastly, we did not explore the differences between firms in terms of organizational culture. Future research should also study the impact of different firm-wide cultures on information sharing and decision-making types to extend knowledge in the BI&A era.

3.3.4 Paper#7. The role of business analytics capabilities in bolstering firms' agility and performance

- Ashrafi, A., **Zare Ravasan, A.,** Trkman, P., & Afshari, S. (2019). *The role of business analytics capabilities in bolstering firms' agility and performance.* International Journal of Information Management. 47. 1-15.
- **Contribution (30%):** I have contributed to this paper in the problem statement, conceptual model development, and data analysis.

BI&A is known as 'competitive differentiators,' and both professional press and academic research consistently demonstrate a positive relationship between BI&A and organizational performance (Ramakrishnan, Jones, & Sidorova, 2012; Viaene & Van den Bunder, 2011). However, how BI&A influences performance is not entirely clear and calls for further research (Abbasi, Sarker, & Chiang, 2016b; Côrte-Real, Oliveira, & Ruivo, 2017). Earlier papers on this topic have established a generally positive impact on performance (Gupta & George, 2016; Trkman et al., 2010), investigated the availability, quality, and use of information (Popovič et al., 2012), or presented the benefits stemming therefrom (Yichuan Wang, Kung, & Byrd, 2018) without investigating the path of influence. Thus, while there is substantial evidence that investments in business analytics can create value, the way in which BI&A leads to value needs deeper analysis (Sharma, Mithas, & Kankanhalli, 2014a). In recent years, several attempts have been made to address this issue (Akter, Fosso Wamba, Gunasekaran, Dubey, & Childe, 2016; Fosso Wamba et al., 2017; Ji-fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017; Torres, Sidorova, & Jones, 2018).

Several interconnected issues influence whether enhanced BI&A capabilities influence a firm's performance (Holsapple et al., 2014). While BI&A can impact the quality of the information in an organization, innovation capability (the ability of an organization to perform innovative practices) is equally important (G. Wang, Dou, Zhu, & Zhou, 2015).

Both then improve the firm's agility specified as the ability to sense and react to opportunities and threats with ease, speed, and dexterity (Tallon & Pinsonneault, 2011).

Still, the firm's agility is not a final objective in itself so much as the required means for achieving and preserving a competitive advantage in a turbulent market (Sherehiy, Karwowski, & Layer, 2007). It is thus needed to examine further the relationship between agility and firm performance under the moderating effect of technological (Trkman & McCormack, 2009) and market turbulence (Jaworski & Kohli, 1993). An interesting question remains as to whether and to what extent market and technological turbulence moderate the relationship between BI&A-enabled firm agility and firm performance. The purpose of the present study is to understand better the influence of BI&A capabilities on firm agility and performance in the presence of environmental turbulence. Specifically, the research model seeks to address the following research questions:

- RQ1. How does BI&A contribute to firm agility and performance?
- RQ2. How does environmental turbulence influence the link between firm agility and performance?

To answer these questions, a conceptual model is proposed to investigate the impact of BI&A on firm agility and performance by exploring the quality of information and innovation capability. This research also aims to find out the extent to which environmental turbulence moderates the link between firm agility and performance. A PLS analysis on survey data of 154 Iranian firms is conducted to validate the model.

The study has several limitations. First, due to this study's cross-sectional nature, we cannot fully understand the dynamics among BA capabilities, agility, and performance over time. Second, we conducted the study only within one developing country. Third, BI&A is a relatively new term, and there does not seem to be an established academic definition (Bichler, Heinzl, & van der Aalst, 2017). Reviewing the literature shows that

BI&A includes several functions and tools to support the strategic decision-making process by preparing an appropriate decision-support environment; the present paper only mentioned BI&A on a conceptual level and did not delve into the functional details. Thus, the paper could be criticized for its discriminatory power for different types of BI&A capabilities within a firm.

This research provides several topics for future studies. First, subsequent studies could replicate this research in other contexts (e.g., developed countries) and compare the results with this study or use a longitudinal study to address the limitations of the cross-sectional nature of this study. In-depth case studies would also be beneficial to provide a more complete understanding. In addition, further research could examine other possible ways in which BI&A capabilities increase firms' performance. In all these efforts, it is important to clearly define the BI&A construct in such a way to avoid tautological findings. Further research should acknowledge the specifics of contemporary BI&A applications (i.e., descriptive, predictive, prescriptive applications) and separately analyze the impact of specific analytics methods, techniques, and models, such as data cleansing and data mining methods, on various facets of performance. Such research would provide more specific guidelines on what kind of BI&A a company in a particular situation should focus so that improvements in the performance would be more likely.

3.3.5 Paper#8. Boosting Innovation Performance through Big Data Analytics: An Empirical Investigation on the Role of Firm Agility

- **Zareravasan, A.** (2021). Boosting Innovation Performance through Big Data Analytics: An Empirical Investigation on the Role of Firm Agility. Journal of Information Science, 01655515211047425.
- **Contribution (100%):** I am the sole author of this paper and contributed to all parts.

Past research has mentioned BDA as a crucial pathway for business value creation (Kristoffersen, Mikalef, Blomsma, & Li, 2021; Marjanovic, 2021; Shollo & Galliers, 2016). The pragmatic view of big data is now dominated by data value, which accelerates innovation by generating actionable insights. While it is of great importance among managers to understand how to benefit from BDA in terms of innovation, there are limited efforts to investigate the link between BDA and innovation (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018; Marshall, Mueck, & Shockley, 2015). Managers and practitioners must know exactly how and under which mechanisms using BDA contributes to innovation (indirect effects) (Mikalef, Boura, Lekakos, & Krogstie, 2019; Shollo & Galliers, 2016). To boost innovation performance, BDA literature has considered data-driven culture as a realization process and a sophisticated BDA team as a foundational issue (Grover et al., 2018; Wamba, Queiroz, Wu, & Sivarajah, 2020) that can play a role in those mechanisms. While prior studies have tried to develop our understanding of these two constructs (Fink et al., 2017; Gupta & George, 2016), there is limited knowledge of their roles within the BDA use pathway. Accordingly, this research postulates the roles of data-driven culture and BDA team sophistication to understand the pathways that might facilitate/hinder the alleged relationship. The main logic for considering the two mentioned moderators is that firms cannot solely rely on their technological infrastructure. They should highlight factors like a proficient BDA team and an evidence-based decision-making culture (Grover et al., 2018) to compete in a turbulent market. Concluding the above argument, this research proposes that the immense and undeniable role of BDA team sophistication alongside a data-driven culture within the organization moderate the link between BDA and innovation performance. To sum up, this research aims at answering the following research questions:

- RQ1. Through what mechanisms of mediating and moderating does BDA impact innovation performance?
- RQ2. How do data-driven culture and BDA team sophistication moderate the impact of BDA on innovation performance?

Dynamic capabilities (DC) theory is employed in this research as an overarching theme. DC theory refers to “the ability to integrate, build, and reconfigure internal and external competencies to address rapidly-changing environments” (Teece, Pisano, & Shuen, 1997, p. 517). This theory explains how competitive advantage is achieved and sustained over the long run (Teece, 2007). It helps businesses adjust their resource mix and sustain their competitive advantage (Vaidyanathan & Devaraj, 2008). Using BDA seems necessary to uncover hidden patterns from a vast amount of data, analyze them to better respond to the market changes (Sharma, Mithas, & Kankanhalli, 2014b), and cope with ever-increasing volatility in all aspects of the market. This focus is particularly useful under turbulent environments (Torres et al., 2018). Thus, it is a central theme of the way from BDA to innovation performance. Scholars have conceptualized DC as a higher-order organizational capability by which firms can achieve a business value (Mikalef, Boura, et al., 2019). Firm agility is widely used in the literature as a critical type of DC that enables higher firm performance (e.g., Park, El Sawy, & Fiss, 2017; Sambamurthy, Bharadwaj, & Grover, 2003). Firm agility is the ability to sense innovation opportunities and respond to those opportunities and rapidly reconfigure resources and processes to exploit marketplace conditions (Ashrafi et al., 2019). Having such a capability is crucial for surviving and thriving in high-velocity environments (Pavlou & El Sawy, 2011). On this basis, this research articulated the concept of firm agility, with three main dimensions as (1) sensing, (2) decision-making, and (3) acting (Park et al., 2017). Then, this research intends to unlock the black box on how BDA impacts innovation performance. In response, a survey of 185 firms is conducted, and data is analyzed using PLS approach.

This study provides several contributions to the theory. First, the current paper is established based on the DC theory to explain better how firms achieve higher innovation performance using BDA. Second, this study is the first shot at understanding the particular roles of data-driven culture and BDA team sophistication within the firm. Third, this research finds out that the BDA team sophistication moderates the link from BDA use to sensing agility. Forth, our findings state that the BDA team sophistication does not moderate the relationship between sensing agility and decision-making agility. Nevertheless, this study has some limitations. First, a questionnaire-based survey is used to validate the research model at one specific time (cross-sectional data), so one cannot understand the constructs' dynamics over time. Therefore, it is recommended that upcoming research conduct longitudinal research to support further the links provided in the nomological model by looking at it over a while. Second, this research collected the required data from Iranian firms. Future research could gather data from other countries to determine possible differences, such as country-level issues that might influence the proposed relationships and findings. Third, to assess the "BDA use" construct, this research highlights the second part (use) rather than the types of technologies used in each firm. Thus, it would be useful for future research to develop or use other questions to cover this issue. Such an approach can also help scholars know the relationships between specific BDA technology and its consequences. Fourth, only BDA team sophistication and data-driven culture are used as moderators. Subsequent studies could investigate other possible moderators' roles, such as absorptive capacity or organizational learning, to enrich this field's knowledge. Fifth, this research assessed innovation performance by using perceptual measures on purpose. It is noteworthy that using more objective measures might bring a better understanding of the BDA - innovation performance relationship.

4 Conclusion

This habilitation thesis is organized by a collection of my eight published journal papers around the timely and important topic of the business value of BI&A. A detailed commentary has also been presented illustrating my contributions to each paper, the research concerns addressed and the limitations each research faced in delivering the intended outcomes. To keep the big picture and show how eight published papers are related to each other, a BI&A business value framework of Trieu (2017) is utilized, and each paper is mapped to the related process in the framework. Accordingly, two papers are related to the "BI&A conversion process", one paper is connected to the "BI&A use process", and five papers are associated with the "BI&A competitive process".

In future work, I will focus on two main research streams. First, in line with the GAČR grant project I secured as the Principal Investigator[1], in 2019, I will focus on the effects of firm performance on subsequent IT/IS investment, i.e., closing the loop of IT/IS (including BI&A) investment. One early result of this project is already published in the Journal of Global Information Management (WoS AIS Q3)[2]. Second, I will focus on the potential business value of BI&A's integration with other state-of-the-art technologies such as IoT and Blockchain, especially for digital transformation and disruption of conventional business models. An early result of this is a published research article at the Journal of Computational Design and Engineering (WoS AIS Q2)[3] that proposes an integrated blockchain–IoT–

[1] Closed-loop view of information system business value: bidirectional relationship between IT/IS investments and firm performance (GA20-12081S), Grant Agency of Czech Republic, Period: 1/2020-12/2022.

[2] ZareRavasan, A., & Krčál, M. (2021). A Systematic Literature Review on 30 Years of Empirical Research on Information Systems Business Value. Journal of Global Information Management (JGIM), 29(6), 1-37.

[3] Bamakan, S. M. H., Faregh, N., & ZareRavasan, A. (2021). Di-ANFIS: an integrated blockchain–IoT–big data-enabled framework for evaluating service supply chain performance. Journal of Computational Design and Engineering, 8(2), 676-690.

big data-enabled framework for evaluating service supply chain performance, and another paper published in the International Journal of Blockchains and Cryptocurrencies focusing on Blockchain and digital transformation of insurance business models[1].

Furthermore, I am trying to strengthen my international research team to apply for new basic and applied research projects from local and international grant agencies. Even though some of my recent attempts (at the local and international level) with this aim failed, I hope the experience I gained throughout the process will further assist me in securing new projects soon.

[1] ZareRavasan, A., Krčál, M. and Ashrafi, A. (2021). Blockchain and digital transformation of insurance business models. International Journal of Blockchains and Cryptocurrencies, 2 (3), 222–243.

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Appendix I. Abstracts of the paper collection

A.1 Paper#1

A practical framework for assessing business intelligence competencies of enterprise systems using fuzzy ANP approach

Saeed Rouhani[a], **Ahad Zare Ravasan[b,*]**

[a] University of Tehran, Tehran, Iran, [b] Allameh Tabataba'i University, Tehran, Iran.

Abstract: As traditional concept in management, decision support had a remarkable role in competitiveness or survival of organizations and following, as modern impression, nowadays business intelligence (BI) has various applications in achieving desirable decision supports. Consequently, assessing BI competencies of enterprise systems can enable decision support in firms. This paper presents a practical framework for assessing the business intelligence capabilities of enterprise systems based on a set of novel factors and utilizing fuzzy analytic network process (FANP). Through this, the construct of BI competency is decomposed into three main competency parts including 'managerial', 'technical' and 'system enabler' sub-goals, five main factors and 26 criteria. Using this framework, the BI competency level of enterprise systems can be determined which can help the decision makers to select the enterprise system that best suits organizations' intelligence decision support needs. In order to validate the proposed model, it is applied to a real Iranian international offshore engineering and construction company in the oil industry to select and acquire ERP system. This research provides a complete frame (factors, criteria and procedures) for firms to assess their proposed software and systems in the field of BI competencies and functions.

Keywords: business intelligence; BI; assessment model; fuzzy analytic network process; FANP; enterprise systems; enterprise resource planning; ERP.

Citation: Rouhani, S., & **Zare Ravasan, A.** (2015). A Practical Framework for Assessing Business Intelligence Competencies of Enterprise Systems Using Fuzzy ANP Approach. International Journal of Applied Decision Sciences (IJADS). 8 (1), 52-82.

A.2 Paper#2

Multi-objective Model for Intelligence Evaluation and Selection of Enterprise Systems

Saeed Rouhani[a], **Ahad Zare Ravasan[b,*]**

[a] University of Tehran, Tehran, Iran, [b] Allameh Tabataba'i University, Tehran, Iran.

Abstract: Most organizations still experience a lack of business intelligence (BI) in their decision-making processes when implementing enterprise systems. The current state-of-the-art in decision support takes the intelligence requirements of enterprise systems as important quality aspects into consideration, along with their functional and non-functional needs, but the literature lacks studies on the evaluation of these intelligence requirements. This paper proposes a fuzzy, multi-criteria decision-making procedure and a multi-objective programming model to evaluate and make final decisions about the selection of enterprise systems that also include the requirements of business intelligence in addition to their other goals and requirements. In order to validate the model with a real application, all phases of the approach were applied in the evaluation of the enterprise systems of a company in the oil industry. Companies can use this model to evaluate, select and implement enterprise software and systems that will provide better decision support for their organizational environment.

Keywords: enterprise systems; business intelligence; multi-objective programming; fuzzy evaluation.

Citation: Rouhani, S. & **Zare Ravasan, A**. (2015). *Multi-objective Model for Intelligence Evaluation and Selection of Enterprise Systems*. International Journal of Business Information Systems (IJBIS). 20 (4). 397-426.

A.3 Paper#3

An investigation of BI Implementation Critical Success Factors in Iranian Context

Ahad Zare Ravasan[a,*]**,** Sogol Rabiee Savoji[b]

[a] Allameh Tabataba'i University, Tehran, Iran, [b] MehrAlborz University, Tehran, Iran.

Abstract: Nowadays, many organizations take Business Intelligence systems to improve their decision-making processes. Although many organizations have adopted BI systems, not all of these implementations have been successful. This paper seeks to identify critical success factors (CSFs) that impact on successful implementation of BI systems in organizations. So, at first, through literature review, 26 CSFs were identified. Following that, a questionnaire was developed and then filled out by domain experts who had at least three years of experience in BI implementation projects in Iran. Robust Exploratory Factor Analysis (EFA) was run for data analysis, which finally classified 26 CSFs into four distinct groups termed as "organizational", "human", "project management", and "technical". The results of this study provide a very useful reference for scholars and managers to identify the relevant issues of BI projects in Iran.

Keywords: BI Implementation, Business Intelligence (BI), Critical Success Factors (CSFs), Project Management, Robust Exploratory Factor Analysis (EFA).

Citation: Zare Ravasan, A., & Rabiee Savoji, S. (2014). *An investigation of BI Implementation Critical Success Factors in Iranian Context.* International Journal of Business Intelligence Research (IJBIR). 5(3), 41-57.

A.4 Paper#4

The Impact Model of Business Intelligence on Decision Support and Organizational Benefits

Saeed Rouhani[a,*], Amir Ashrafi[b], **Ahad Zare Ravasan[b],** Samira Afshari[b].

[a] University of Tehran, Tehran, Iran, [b] Allameh Tabataba'i University, Tehran, Iran.

Purpose: Decision support, as a traditional management concept, have had a remarkable role in competitiveness or survival of organizations and nowadays, business intelligence (BI), as a brand modern impression, has various contributions in supporting decision-making process. Although, a variety of benefits are expected to arise from BI functions, researches, and models that determining the effect of BI functions on the decisional and organizational benefits are rare. The purpose of this paper is to study the relationship between BI functions, DS benefits, and organizational benefits in context of decision environment.

Design/methodology/approach: This research conducts a quantitative survey-based study to represent the relationship between BI capabilities, decision support benefits, and organizational benefits in context of decision environment. On this basis, the partial least squares (PLS) technique employs a sample of 228 firms from different industries located in Middle-East countries.

Findings: The findings confirm the existence of meaningful relationship between BI functions, DS benefits, and organizational benefits by supporting 15 out of 16 main hypotheses. Essentially, this research provides an insightful understanding about which capabilities of BI have strongest impact on the outcome benefits.

Originality/value: The results can provide effective and useful insights for investors and business owners to utilize more appropriate BI tools and functions to reach more idealistic organizational advantages. Also it enables managers to better understand the application of BI functions in the process of achieving the specified managerial support benefits.

Keywords: Decision support benefits, Organizational benefits, BI functions, Business intelligence (BI) benefits, Partial least squares (PLS) technique.

Citation: Rouhani, S., Ashrafi, A., **Zare Ravasan, A.**, & Afshari, S. (2016). *The Impact Model of Business Intelligence on Decision Support and Organizational Benefits*. Journal of Enterprise Information Management. 29 (1). 19-50.

A.5 Paper#5

Business Intelligence Systems Adoption Model: An empirical investigation

Saeed Rouhani[a,*], Amir Ashrafi[b], **Ahad Zare Ravasan[c],** Samira Afshari[b].

[a] University of Tehran, Tehran, Iran, [b] Allameh Tabataba'i University, Tehran, Iran, [c] Mehralborz Institute of Higher Education, Tehran, Iran.

Abstract: Decision support and business intelligence systems have been increasingly adopted in organizations, while understanding the nature of affecting factors on such adoption decisions need receiving much academic interest. This article attempts to provide an in-depth analysis toward understanding the critical factors which affect the decision to adopt business intelligence (BI) in the context of banking and financial industry. In this regard, it examines a conceptual model that shows the impacts of different technological, organizational, and environmental factors in the decision to adopt BI by a firm. Structural equation modeling (SEM) was used for data analysis and test the relevant hypothesis. The results of this article which are derived from theoretical discussion of hypothesizes show that from nine hypothesized relationships—perceived tangible and intangible benefits, firm size, organizational readiness, strategy, industry competition and competitors absorptive capacity—affect BIS adoption in the surveyed cases.

Keywords: Adoption Model, Business Intelligence, Partial Least Squares (PLS), TOE Framework.

Citation: Rouhani, S., Ashrafi, A., **Zare Ravasan, A.,** & Afshari, S. (2017). *Business Intelligence Systems Adoption Model: An empirical investigation.* Journal of Organizational and End User Computing (JOEUC). 30(2), 43-70.

A.6 Paper#6

How market orientation contributes to innovation and market performance

Amir Ashrafi[a], **Ahad Zare Ravasan[b,*]**

[a] Allameh Tabataba'i University, Tehran, Iran, [b] Bournemouth University, Poole, UK.

Purpose: Market orientation (MO) (intelligence generation, intelligence dissemination and responsiveness) is known as one of the key concepts in marketing literature. Although prior research has widely focused on the meaning and application of MO, few attempts have been made to explore how market-oriented firms lead to innovation and market performance and what factors actually moderate this relationship. To fill this gap, the present study aims to explore the relationship between MO, innovation and market performance. This study also attempts to examine the intervening role of IT infrastructure, business analytics (BA) capabilities and market turbulence in the proposed model.

Design/methodology/approach: In this study, a questionnaire-based survey was undertaken to test the proposed hypotheses. To verify the proposed theoretical model, partial least squares (PLS)/structured equation modeling (SEM) was performed with 114 valid survey data.

Findings: Despite prior studies which postulated innovation performance as the final outcome of MO (Han et al., 1998; Song et al., 2015), this study focused on innovation performance as a mediating outcome which finally leads to market performance. The statistical results approve the putative relationship which means managers would be able to realize the paramount role of innovation as an integral part of achieving higher market performance. In addition, no support was found for the relationship between intelligence generation and responsiveness. This finding shows that not all obtained information can help managers in the decision-making process.

Originality/value: This study aims to enrich literature by developing a conceptual model to test the link between MO, innovation and market performance. The value of this study is to investigate the roles of flexible IT infrastructure, BA capabilities and market turbulence as the potential moderators in the proposed model. The results advance the understanding of the influence of BA capabilities on the link between intelligence dissemination and responsiveness. Findings also show innovation performance as remarkable and deemed valuable capability, leading to higher performance in marketing-related activities, particularly in highly turbulent markets.

Keywords: Market orientation, Responsiveness, Business analytics capability, Flexible IT infrastructure, Intelligence dissemination, Intelligence generation.

Citation: Ashrafi, A., & **Zare Ravasan, A**. (2018). *How market orientation contributes to innovation and market performance.* Journal of Business and Industrial Marketing. 33 (7). 970-983.

A.7 Paper#7:

The role of business analytics capabilities in bolstering firms' agility and performance

Amir Ashrafi[a], **Ahad Zare Ravasan[b],** Peter Trkman[c,*], Samira Afshari[a]

[a] Allameh Tabataba'i University, Tehran, Iran, [b] Masaryk University, Brno, Czech Republic, [c] University of Ljubljana, Slovenia

Abstract

Many companies invest considerable resources in developing Business Analytics (BA) capabilities to improve their performance. BA can affect performance in many different ways. This paper analyses how BA capabilities affect firms' agility through information quality and innovative capability. Furthermore, it studies the moderating role of environmental turbulence, both technological and in the market. The proposed model was tested using statistical data from 154 firms with two respondents (CEO and CIO) from each firm. The data were analyzed using Partial Least Squares (PLS)/Structured Equation Modelling (SEM). Our results indicate that BA capabilities strongly impact a firm's agility through an increase in information quality and innovative capability. We also discuss that both market and technological turbulence moderate the influence of firms' agility on firms' performance.

Keywords: Business analytics, Agility, Information quality, Innovative capability, Environmental turbulence, Partial least squares.

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A.8 Paper#8

Boosting Innovation Performance through Big Data Analytics: An Empirical Investigation on the Role of Firm Agility

Ahad ZareRavasan[a,*]

[a] Masaryk University, Brno, Czech Republic

Abstract: While past studies proposed the role of Big Data Analytics (BDA) as one of the primary pathways to business value creation, current knowledge on the link between BDA and innovation performance remains limited. In this regard, the present study intends to fill this research gap by developing a theoretical framework for understanding how and under which mechanisms BDA influences innovation performance. Firm agility (conceptualized as sensing agility, decision-making agility, and acting agility) is used in this research as the mediator between BDA and innovation performance. Besides, this research conceptualizes two moderating variables; data-driven culture and BDA team sophistication. This study employs Partial Least Squares (PLS) to test and validate the proposed hypotheses using survey data of 185 firms. The results show that firm agility significantly mediates the link between BDA use and innovation performance. Besides, the results suggest that data-driven culture moderates the relation between sensing agility and decision-making agility. This research also supports the moderating role of BDA team sophistication on the link between BDA use and sensing agility.

Keywords: Big Data Analytics (BDA), Big Data Business Value, Dynamic Capabilities (DC) theory, Agility, BDA Team Sophistication, Data-driven Culture, Innovation Performance.

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Appendix II. Full text of the paper collection

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