MASTER THESIS EXPOSÉ

The influence of Business Intelligence systems on organizational performance: a literature review of empirical studies

Submitted by

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ABSTRACT

Title: The influence of Business Intelligence systems on organizational performance: a literature review of empirical studies

Background: Business Intelligence systems have acquired growing importance in the last decades. Taking an action in an informed and timely manner has become crucial in today's competitive economic environment. Thereby managers and decision makers of various organizations strive to acquire the needed competences to appropriately master business intelligence tools. Hand in hand with the growing interest of the practitioner environment, academics have worked hard to conduct empirical studies to analyze and demonstrate the effects of business intelligence systems on companies and organizations of various kinds. Interestingly, a literature review aimed at gathering and presenting the results of such studies has not yet been drawn up.

Purpose: The objective of this study is to draft a literature review to collect and present the results of the empirical papers written in the last 9 years that investigate the effects of Business Intelligence systems on organizations.

Method: The methodology consists of a literature review prepared by selecting the articles from the online research portal "Web of Science". The articles object of the analysis were selected according to explicit criteria through a specific query that allowed to obtain a sufficient number of articles for an exhaustive analysis of the topic.

Keywords: Business Intelligence, Organizations, Organizational Performance, Management, Literature Review

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1.INTRODUCTION

1.1 Background and problem statement

Business intelligence has been defined in different ways according to the moment of the definition and the purpose of the author. Azvine et al. (2006) define business intelligence as follows: "Business Intelligence is all about capturing, accessing, understanding, analyzing and converting one of the fundamental and most precious assets of the company, represented by the raw data, into active information in order to improve business". From this definition the importance of business intelligence is clearly understandable. Due to the ever-changing dynamics of the global markets leveraged by technological innovation, organizations seek to gain competitive advantage, and thereby try to find new ways to succeed in their industries. In such a context, Business Intelligence tools gain primary importance and as a result in the last decades several scholars tried to investigate whether a relationship between Business Intelligence and organizational performance exist and, if it is the case, to understand if such a relationship is positive (Fink, Yogev & Even, 2017; Lautenbach, Johnston & Adeniran-Ogundipe, 2017; Popovic, Hackney, Coelho & Jaklic, 2014; Rouhani, Ashrafi, Zare Ravasan & Afshari, 2016; Silahtaroglu & Alayoglu, 2016). To investigate the positive effect of Business Intelligence on organizations, the methodology of the studies conducted so far by the scholarship is various and it ranges from literature reviews and conceptual works to empirical papers and case studies (Bach, Jaklic & Susa Vugec, 2018; Gauzelin & Bentz, 2017; Owusu, 2017). Indeed, literature reviews that investigate the Business Intelligence domain from a general standpoint have been extensively conducted (Azevedo & Santos, 2009; Chuah & Wong, 2011; Mishra, Luo, Hazen, Hassini & Foropon, 2018; Popovic, Hackney, Coelho & Jaklic, 2014; Watson, 2009). However, despite the great number of materials that can be found in terms of scholarship production, there is a lack of systematic literature reviews that focus exclusively on empirical studies.

The aim of this study is thereby to address such a gap and to provide a literature review of empirical studies that analyze Business Intelligence impact on organizations. The literature review will serve as a preliminary work that can be used as a ground point for further development and research.

1.2 Assumptions

In the following paragraphs, assumptions underlying this study are presented.

Several studies have shown the existence of a positive relationship between the implementation of business intelligence systems and the different aspects of organizational performance. For example,

Owusu (2017) in his study shows how business intelligence systems have a favorable impact on the organizational performance of Ghanaian banks. Similarly, Gauzelin and Bentz (2017) obtain similar results in their analysis of the effects of business intelligence systems in small and medium-sized French companies. Moreover, multiple empirical articles dealing with Business Intelligence integrate their content with research concerning the specific elements that make successful the adoption of a Business Intelligence system in an organization (Antoniadis, Tsiakiris & Tsopogloy, 2015; Eybers & Giannakopoulos, 2015; Mulyani , Darma & Sukmadilaga, 2016; Villamarin-Garcia & Diaz Pinzon, 2017). As an example, Villamarin-Garcia & Diaz Pinzon (2017) identify 13 factors that affect a successful implementation of a Business Intelligence system. For their part, Eybers and Giannakopoulos (2015) identify three different groups of success factors for Business Intelligence, namely organizational, process or technological factors. For these reasons, the first assumption of this work is the following:

H1: Business Intelligence positively impacts organizational performance.

Another element that is often identified as part of the positive outcomes deriving from the implementation of business intelligence systems in organizations is the increase in the effectiveness of decision-making processes. Among the various authors who directly mention the positive effects that business intelligence systems have on decision-making processes, we mention Frisk and Bannister (2017), Gauzelin and Bentz (2017), Huie (2016) and Kiani Mavi and Standing (2018). Consequently, it was decided to choose the following assumption:

H2: Business Intelligence systems improve decision making process effectiveness within organizations.

1.3 Significance of the study

This study has implication both on the research and the practitioner side. From an academic point of view, this study aims to create a literature review conducted with methodological rigor of empirical articles useful to understand the interrelation between business intelligence systems and organizations and at the same time to prepare a starting point for further research. In fact, this preliminary study could have the potential to form the basis for similarly structured scientific works aimed at exploring the same subjects in depth. Wishing to focus on the benefits that this work could have in terms of contribution for practitioners, this study, being a literature review of empirical articles (and therefore

of primary sources), could provide experts in the business intelligence sector and managers wishing to invest in this sense a useful overview of the effects of business intelligence systems on companies. Furthermore, given the fact that often empirical articles do not limit themselves to analyzing the effects of business intelligence systems on organizations but offer insights and advice on how to optimize certain situations that can be improved, this work could be consulted by managers and professionals as a collection of best practices on the use of business intelligence systems in companies and more generally in any type of organization.

2.THEORETICAL FRAMEWORK

2.1 Theoretical background

The aim of the following section is to provide theoretical foundation for this work. The concepts introduced below, were retrieved from the theoretical backgrounds of some of the empirical studies that will form the object of the literature review. First, an overview of Business Intelligence definitions is presented. Thereafter, models used to assess the role of Business Intelligence within organizations are introduced. In particular, empirical papers that analyze the impact of Business Intelligence in organizations often develop their studies within the framework of two major concepts: organizational performance and maturity models (Bach, Jaklic & Susa Vugec, 2018). As a result, organizational performance concept is presented, and two maturity models are explained. Moreover, in the empirical studies that will be the object of the analysis, structural equation modeling is often used (Caseiro & Coelho, 2018; Fink et al., 2016; Gasemaghaei & Calic, 2019; Knabke & Olbrich, 2017; Mishra et al., 2018). For this reason, it was considered appropriate to include a brief explanation of this statistical method within the theoretical framework.

2.2 Definitions of Business Intelligence

Business Intelligence is a term which is often used to describe different activities usually linked to those processes and technologies implemented to collect, store and analyze data and more in general information with the purpose of improving and supporting decision making (Caseiro & Coelho, 2019). Indeed, references to the term Business Intelligence as to an umbrella term are very widespread in the scholarship (Caseiro & Coelho, 2019; Turban, Sharda & Delen, 2011; Wanda & Stian, 2015; Watson, 2009). Nevertheless, several definitions of Business Intelligence can be found across literature. Azvine et al. (2006) define business intelligence as follows: "Business Intelligence is all about capturing, accessing, understanding, analyzing and converting one of the fundamental and most precious assets of the company, represented by the raw data, into active information in order to improve business". According to Azevedo and Santos (2009) Business Intelligence is rooted in the Decision Support Systems (DSS) discipline which in turn is a part of the Information Systems research area. Azevedo and Santos (2009) define Business Intelligence as "the Information Systems aimed at integrating structured and unstructured data in order to convert it into useful information and knowledge, upon which business managers can make more informed and consequently better decisions". In their study, Fink, Yogev and Even (2016) refer to Business Intelligence Systems as systems that "aim at improving the quality of information used in the decision-making process as a consequence of simplification of storage, identification, and analysis of information. They offer a

comprehensive view of the entire organization, permit the analysis of business activities from multiple perspectives, and enable rapid reactions to changes in the business environment". Rouhani, Asgari and Mirhosseini (2012) state that "Business intelligence is the process of using information and analyzing them in order to support decision-making and using different methods helping organizations to forecast the behavior of competitors, suppliers, customers and environments to stay alive and survive in a global economy". Furthermore, Negash and Gray (2008) define Business Intelligence as "systems that combine data gathering, data storage and knowledge management with analysis to evaluate complex corporate and competitive information for presentation to planners and decision makers, with the objective of improving the timeliness and the quality of the input to the decision process".

As can be seen, even though the definitions come from different sources, all of them elicit a positive picture of Business Intelligence and Business Intelligence Systems. Indeed, all the definitions evoke terms such as "simplification", "better decisions" or "improved quality" meaning that a commonly accepted favorable value is conferred to Business Intelligence among scholars. This is consistent with the initial assumption that Business Intelligence has a positive impact on organizations and decision-making process. The different although similar definitions of Business Intelligence are helpful to better understand the framework within the literature review will be implemented for the reason why the clarification of concepts is essential to have a full understanding of the topic that is being treated.

Because of the lack of uniformed definition of Business Intelligence, for the purpose of this work it is considered to be more appropriate to present an overview of the different definitions provided by the literature and rather to comment the definitions retrieved from the empirical papers (which will be analyzed) when worth of mention.

2.3 Maturity Models: TDWI's Business Intelligence Maturity Model

Maturity models are tools designed to give a rapid overview of the state of the art of the people competencies in a certain area within an organization (Hribar Rajteric, 2010; Popovic et al., 2012). In particular, in the Business Intelligence context, different models have been developed. The TDWI's Business Intelligence Maturity Model developed by Wayne Eckerson (Eckerson, 2007) is an example of such a tool. The model aims to assess the organization principally from a technical perspective (Brooks, El Gayar & Sarnikar, 2015; Hribar Rajteric, 2010). More specifically, the model evaluates eight key areas in the Business Intelligence: Scope, Sponsorship, Funding, Value,

Architecture, Data, Development and Delivery. Each of the eight aspects is assessed through the following five grade scale (Eckerson, 2007; Hribar Rajteric, 2010):

- Infant is the first level and it is in turn composed of two phases: Prenatal and Infant. In the Prenatal phase, only some operational reporting is performed but no Datawarehouse is existing within the organization. In the Infant phase, spreadmarts (spreadsheets or desktop databases) are present and they contain specific sets of data but are not connected between each other through analytical systems. There is no possibility for the company to have a clear view of all the events of the company.

- Child is the second level of the scale. At this level the organization usually buys a first interactive reporting tool, workers start to be able to analyze data and some data analysis is performed to take insights from the past business decisions. The analysis and data report are usually carried out at a departmental level and does not involve the entire organization.

- Teenager is the third level of the grade scale. At this level software solutions for Business Intelligence are developed and centralized Datawarehouse is created. Thanks to centralization of Datawarehouse, company-wide analysis can be performed. Customized dashboards are introduced for different users and the use of BI is widespread across the employees.

- Adult is the fourth phase of the grade scale. At this level often the company creates a special Business Intelligence team independent from the organizational structure that reports directly to the executives. The Datawarehouse is fully loaded with all the data of the company and designed in such a way that it allows real time data collection as well as different operations from various users. More advanced prediction and data mining techniques are implemented across the company.

- Sage. At this level the Business Intelligence and IT are fully aligned and cooperative, the number of BI users is dramatically increased within the organization and the development of new customized BI tools is delegated to basic organizational units often called Centers of Excellence (COE) which operate at a department or local level.

2.4 Maturity Models: Gartner's Maturity Model for Business Intelligence and Performance Management

Another maturity model to assess Business Intelligence maturity is the Gartner's Maturity Model for Business Intelligence and Performance Management. This model was developed by Gartner (Rayner

& Schlegel, 2008). and it presents five levels of maturity: unaware, tactical, focused, strategic and pervasive (Newman & Logan, 2008). Compared to the previous Eckerson's model, it is less technical and provides an overview of Business Intelligence maturity from a business standpoint (Chuah & Wong, 2011; Hribar Rajteric, 2010; Shaaban, Helmy, Khedir & Nasr, 2011). The main features of each level are the following:

- Unaware. At this level the company does not have defined metrics for performance management, spreadsheets are used but reporting tools are almost not existing. The importance of Business Intelligence is underestimated, and Information Management is a matter of IT department with no involvement of the rest of the organization.
- Tactical. At this level companies start to invest into Business Intelligence. Metrics and performance indicators are used at a department level. At this level, organizations often use off-the shelf software to fulfill company requirements. Employees are not skilled enough to fully understand the system and thereby to enjoy its benefits.
- Focused. In the third maturity level benefits of Business Intelligence start to become tangible. Despite this, the Business Intelligence usage is still limited to a part of the organization. Usually the aim of the systems at this level is to optimize the efficiency of the single departments but there is a lack of enterprise-wide vision. There is a lack of data integration at a company level and Business Intelligence Competency Centers (BICC) where IT and business experts are gathered to fulfil users' needs start to be formed within the organization.
- Strategic. At this level the company has a strategy for Business Intelligence development, top management is aware of the Business Intelligence potential benefits and data quality is constantly under supervision. Strategic decision-making takes full advantage of Business Intelligence information and employees are trained for data processing.
- Pervasive. At this level Business Intelligence becomes pervasive in all business processes. Employees are adequately trained to perform a broad range of activities related to data process and analysis. Results can be easily measured and are clearly linked to specific business goals.

Gartner (Newman & Logan, 2008) uses this model to assess Business Intelligence maturity both at a company and at a department level. Results often shows that companies have different departments at different level of maturity. This can result in bottlenecks and inefficiencies at a company level, thereby the Gartner's Maturity Model can help to spot these inefficiencies and improve the business performance of the company (Hribar Rajteric, 2010; Lauthenbach, Johnston & Adeniran-Ogundipe, 2017).

2.5 Organizational performance and organizational effectiveness

Organizational performance is referred as to the total outcome of three interrelated and complementary performances, namely: financial performance, product market performance and shareholder return (Richard, Yip & Devinney 2009; Caseiro & Coelho, 2019). On the other hand, organizational effectiveness is considered a broader concept that include the organizational performance components as well as other important elements that are not associated with mere economic evaluation such as corporate social responsibility (Richard, Yip & Devinney 2009). Both measures are used to assess the performance of a company from different standpoints. Due to its more specific nature and economic perspective, organizational performance is more often mentioned in management literature (Gavrea, Ilies & Stegerean, 2011; Richard, Yip & Devinney 2009).

Organizational performance can be assessed by three typologies of objective measures: accounting measures, financial measures and mixed measures (Richard, Yip & Devinney 2009). Accounting measures include (among others) cash flow from operations, EBIT, market share, Net operating profits, ROA, ROE, ROI. The most prominent financial measures are Beta coefficient, earnings per share, Jensen's alpha, market capitalization, P/E ratio and stock price. When it comes to mixed measures it is worth to cite the balanced scorecard, cash flow per share, discounted cash flow, eva and the internal rate of return (Richard, Yip & Devinney 2009). As mentioned before, organizational performance measures are employed in the management research area. Indeed, they are extensively used to assess Business Intelligence impact on organizations (Bach, Jaklic & Susa Vugec, 2018; Fink, Yogev & Even, 2017; Gauzelin & Bentz 2017; Owusu, 2017; Popovic, Hackney, Coelho & Jaklic, 2014).

2.6 Structural Equation Modeling (SEM)

Structural Equation Models (or SEM, an acronym for Structural Equation Modeling) represent a general statistical modeling technique aimed at establishing and quantifying relations between variables (Bag, 2015). A key feature, which has made the technique much appreciated for the study of complex phenomena in different areas, is the ability to measure "latent variables" (or constructs, or factors), not directly observable, through a set of observable variables, and therefore measurable. Added to this is the possibility of studying contextually the causal relationships between variables.

The use of structural equation modeling is particularly widespread in the social sciences and the study of the relationship between business intelligence and organization is no exception (Caseiro & Coelho, 2018; Fink et al., 2016; Gasemaghaei & Calic, 2019; Knabke & Olbrich, 2017; Mishra et al., 2018). For example, Rouhani et al. (2016) in their analysis of organizational benefits of business intelligence conducted on a sample of 228 companies from different sectors in the Middle East, used structural equation modeling to present and validate their conceptual model and the hypotheses of their study. The model is presented in Figure 1.
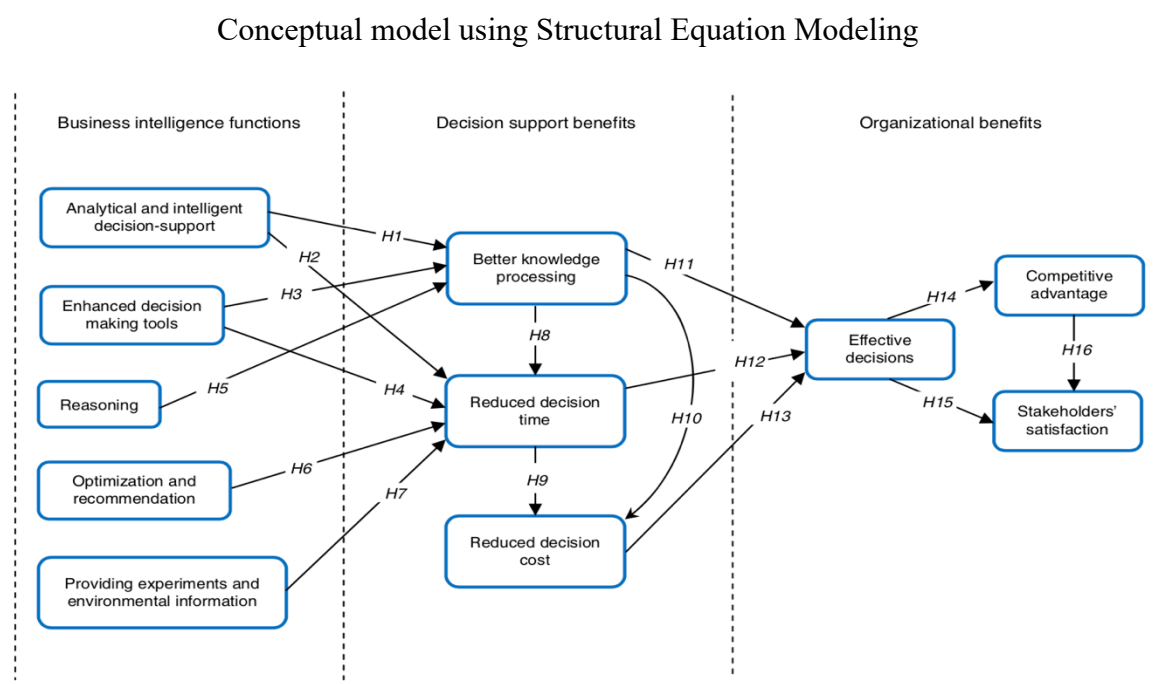
Conceptual model using Structural Equation Modeling

Figure 1 Conceptual model using Structural Equation Modeling. Adapted from *The impact model of business intelligence on decision support and organizational benefits*. Retrieved from http://dx.doi.org/10.1108/JEIM-12-2014-0126

The figure above shows the relationship between business intelligence functions and decision support systems which in turn affect organizational benefits. Each function is linked to the next by a causal relationship that represents the constructs (or latent variables), which subsequently have been assessed using the least squares method (Rouhani et al., 2016).

3.LITERATURE REVIEW

Table 1

Literature Review

#	Title	Author	Year published	Contribution
1	The influence of Business Intelligence capacity, network learning and innovativeness on startup performance	Nuno Caseiro, Arnaldo Coelho	2019	Investigates the direct and indirect effects of Business Intelligence on performance of a sample of 228 startups from different European countries using Structural Equation Modeling (SEM)
2	Organisational capabilities that enable big data and predictive analytics diffusion and organisational performance	Deepa Mishra, Zongwei Luo, Benjamin Hazen, Elkafi Hassini, Cyril Foropon	2018	Tests how Information Technology deployment and HR capabilities affect organizational performance through Big Data and Predictive Analytics. It applies structural equation modeling on the survey data collected from 159 Indian companies
3	Cause and effect analysis of business intelligence (BI) benefits with fuzzy DEMATEL	Reza Kiani Mavi, Craig Standing	2018	Interviews 10 expert professionals and identifies eighteen Business Intelligence benefits in four dimensions of organizational benefits, business partners relation

				benefits, internal process efficiency benefits and customer intelligence benefits.
4	Understanding impact of business intelligence to organizational performance using cluster analysis: does culture matter?	Mirjana Pejic Bach, Jurij Jaklic, Dalia Susa Vugec	2018	Analyzes the impact of the level of business intelligence maturity to organizational performance of the company. It collects data through questionnaires on a sample of 177 Croatian and Slovenian companies and analyzes them by the use of Cluster analysis.
5	Key success factors to business intelligence solution implementation	José Manuel Villamarin-Garcia, Beatriz Helena Diaz Pinzon	2017	Identifies thirteen key success factors to Business Intelligence solution implementation and assess these factors along with experts in the domain of Business Intelligence.
6	Business Intelligence systems and bank performance in Ghana: the balanced scorecard approach.	Acheampong Owusu	2017	Empirically evaluates the impact of Business Intelligence adoption in banks in Ghana through a survey on a sample of 130 executives that is analyzed through Structural Equation Modeling (SEM).
7	An examination of the impact of Business Intelligence systems on	Sophian Gauzelin, Hugo Bentz	2017	Examines the impact of business intelligence

	organizational decision making and performance: the case of France			systems on organizational decision-making and performance through interviews to 200 members of ten small-medium sized enterprises.
8	Factors influencing Business Intelligence and analytics usage extent in South African organizations	P. Lautenbach, K. Johnston, T. Adeniran-Ogundipe	2017	Examines factors influencing Business Intelligence use within organizations. It conducts the research on a sample of 72 IT and BI managers in South African organizations.
9	Business Intelligence and Organizational Learning: an empirical investigation of value creation process	Lior Fink, Nir Yogev, Adir Even	2016	Develops and tests a model of Business Intelligence value creation. It tests the model through interviews in three firms and through a survey on a sample of 159 Business Intelligence managers.
10	The impact model of business intelligence on decision support and organizational benefits	Saeed Rouhani, Amir Ashrafi, Ahad Zare Ravasan, Samira Afshari	2016	Studies the relationship between Business Intelligence functions, Decision Support benefits and organizational benefits in the context of decision environment. Employs the Structural Equation Modeling with PLS technique on a sample of 228 firms from

				different industries in the Middle East.
11	Identifying Critical Success Factors (CSFs) for Business Intelligence Systems	Sunet Eybers, Apostolos Giannakopoulos	2015	Identifies critical success factors for successful implementation of Business Intelligence Systems. Conducts a qualitative study consisting in interviews from four organizations from various industries.
12	On being "systematic" in literature reviews in IS	Sebastian K. Boell, Dubravka Cecez-Kecmanovic	2015	Provides an analysis of systematic literature reviews in the Information Systems domain.
13	Synthesizing information systems knowledge: a typology of literature reviews	Guy Paré, Marie-Claude Trudel, Mirou Jaana, Spyros Kitsiou	2015	Assesses 139 reviews in IS journals and draws a classification of literature review typologies in the Information Systems research area.
14	Towards Business Intelligence systems success: Effects of maturity and culture on analytical decision making	Ales Popovic, Ray Hackney, Pedro Simoes Coelho, Jurij Jaklic	2012	Conducts a quantitative survey-based study to examine the relationship between maturity, information quality, analytical decision-making culture, and the use of information for decision-making as significant elements of the success of Business Intelligence systems from

				a sample of 181 medium and large organizations.
15	Overview of Business Intelligence Maturity Models	Irena Hribar Rajteric	2010	Describes and analyzes six different maturity models that can be used for business intelligence systems maturity assessment.
16	Business Intelligence, state of the art, trends and open issues	Ana Azevedo, Manuel Filipe Santos	2009	Presents a general overview of various aspects of Business Intelligence research area. It provides a definition of Business intelligence.
17	Measuring Organizational Performance: towards Methodological Best Practice	Pierre Richard, Timothy Devinney, George Yip	2009	Reviews past studies and conceptualize organizational performance. Provides a definition of organizational performance.

4.METHODOLOGY

4.1 Introduction

The methodology used in this dissertation consists in a literature review. The aim of this introduction is to present the structure of the methodology chapter. In the paragraphs below, a brief prelude about what literature review means in scientific academic work and more specifically in the Information Systems domain is conducted. After this, the subsequent section describes in detail the methodology of this work.

4.2 Literature Review

A literature review can be defined as a systematic, explicit, comprehensive and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners (Okoli and Schabram, 2010). Literature reviews are of foremost importance in the academic environment because of the critical role that they play in helping scholars, practitioners and graduate students to find, analyze and evaluate empirical papers or articles of any kind, thereby giving them the possibility to pursue their goals, be they to keep up to date with a topic, start a new research or evaluate the state of the art of a subject (Paré, Trudel, Jaana & Kitsou, 2015). Literature reviews are crucial for several reasons the most important being to identify what has been written on a particular topic, to understand the state of the art of specific research area, to cumulate and synthetize the results of a group of empirical or conceptual studies, to develop new theories and to identify new subjects or future research directions about an existing topic (Alvesson & Sandberg, 2011; Boell & Cecez-Kecmanovic, 2015; LePine & Wilcox-King, 2010; Paré et al., 2015). In the Information Systems (IS) domain, there are several ways to classify literature reviews (Boell & Cecez-Kecmanovic, 2015). Among others, a classification of literature reviews in the IS can be done by distinguishing literature reviews in nine literature review typologies (Paré et al., 2015):

- Narrative reviews attempt to summarize what has been written on a particular topic.
- Descriptive reviews aim to find patterns in a body of empirical studies in a specific research area with respect to pre-existing propositions and/or assumptions.
- Scoping/mapping reviews determine the size of the existing literature on a subject.

- Meta-analyses analyze two or more studies by the use of data extraction techniques and statistical methods.
- Qualitative-systematic reviews are similar to meta analyses, but they use narrative techniques rather than statistical approaches to analyze the data.
- Umbrella reviews are also called reviews of reviews since they integrate results of other reviews (either quantitative or qualitative).
- Theoretical reviews attempt to create a conceptual framework or theoretical model.
- Realist reviews are developed to inform, enhance, extend or supplement existing reviews and they are often structured in such a way that gives suggestions for decision making policies.
- Critical reviews try to reveal weaknesses, contradictions or inconsistencies in the literature on a broad topic.

Having given an overview of literature reviews and their objectives in the Information Systems research area, in the following paragraphs the methodological approach used in this work is presented.

4.3 Data collection and method implementation

As anticipated in the introduction, the methodology consists in a literature review of empirical studies. More specifically, the research method is implemented through three main phases, namely literature retrieval (data collection), document analysis and results presentation. The first phase (data collection) should be particularly emphasized for the reason that it includes the database through which the data collection is performed as well as the literature selection and exclusion criteria, being these the elements that would allow this study to be replicated by another researcher and making thereby the methodology worthy of scientific rigor (Drummond, 2018; Filder and Wilcox, 2018). The data collection is implemented by the retrieval of relevant literature using the on-line database Web of Science (WoS). The query developed to select the literature is the following: ("business intelligence") AND (manag* OR decision OR organi*) filtered by "Topic" in the search form. The time span of the research is from the year 2013 to the year 2019. The categories selected for the research are Management, Business, Economics, Social Science Interdisciplinary, Business Finance. The run of the query at the time of writing provides 456 results. The results will be scanned by reading the abstract of each article with the aim to select about 50 empirical papers suited for the analysis. Hereinafter justification for each of the data collection process elements are provided. The choice of using Web of Science as a database for literature retrieval is due to the scientific reliability that is accorded to it by the academic community (Chirici, 2012). In particular, Google Scholar is excluded because despite its extended coverage non-scholarly sources, erroneous citation data and omissions

may be present as argued by other authors (Chirici, 2012; Jacso, 2005; Meho & Yang, 2007; Mikki, 2009). The query was selected after several attempts. For instance, at the beginning a query that included "business analytics" in the keywords was tried but the amount of results was beyond the scope of this work. Also, the business intelligence keyword was tested without quotation marks (meaning that the results would have included a larger number of articles not always strictly related to the Business Intelligence research area) and again the results were not narrow enough to set an acceptable starting point for the analysis. The time span 2013-2019 was chosen because, due to the recent nature of the topic, it seemed wiser to consider the newest studies for the review. Besides, when filtered by year, the results show a sharp increase of literature production from the year 2012 to the year 2013 supporting the decision to consider 2013 as the starting year for the analysis. Another important element of the data collection phase is the category section. The categories were selected among the aforementioned ones because of their managerial/business nature. Categories such as Computer Science or Electrical Engineering were purposely excluded because of their technical nature that is not suited to the objective of this work. The document analysis will be performed by reading the selected articles and a presentation of both quantitative and qualitative results will be carried out. For instance, quantitative data such as the frequency with which a certain event occurred in the papers will be presented as well as insights about the conclusions of the authors in the different articles. Overall, if assessed trough the literature review typology lens presented in the introduction, the typology of this review can be reconducted to a descriptive literature review.

5.WORKPLAN

Table 2

Workplan

Dates	Objective
15/11 – 30/11	Literature retrieval and research, selection of articles by reading the abstracts
1/12 – 15/12	Quantitative and qualitative analysis and presentation of the results of the literature review retrieval.
16/12 – 31/12	Writing the discussion and conclusion section
1/01 – 12/01	Conclusions refinement and thesis submission

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