The impact of Business Intelligence Visual Tools on Decision Making: a user perspective

Simone Stramenga

Abstract

Title: The impact of Business Intelligence Visual Tools on Decision Making: a user perspective.

Background: In recent years, the even greater generation of data from every kind of source has led companies to acquire new systems and tools such as Business Intelligence, in order to manage and extrapolate insights from them. Among the different functions of Business Intelligence Systems, the support of decision-making results to be one of the most fundamental, yet neither literature nor practice managed to understand the key factors to fully benefit BI potentials.

Aim: The aim of this study will be the validation of a model to retrieve a better insight from the user perspective regarding the BI support function and effectivity on decision making through its visual tools.

Methodology: A quantitative study will be conducted through the use of an online self-administered questionnaire. The target sample refers to any kind of professional, either employ or manger using BI tools with monthly or weekly rate in order to support their functions and take decisions.

Contributions: The study contributes to the literature body regarding Business Intelligence systems Adoption, Utilisation and Success, focusing on the impact of BI visual tools on the decision-making process from the user perspective. Moreover, the research practically contributes highlighting to companies the fundamental cognitive elements of Business Intelligence which might be leveraged to fully benefit its potential.

Keywords: Business Intelligence, Data Visualisation, Information Systems, Cognitive Load, Decision making, Information Quality, User Satisfaction.

Table of Contents

List of abbreviations

BI: Business Intelligence

BIS: Business Intelligence Systems

IS: Information systems

IQ: Information Quality

AUS: Adoption, Utilisation, Success

List of figures

List of tables

1. Introduction

Due to the even faster accumulation of data generated within and outside organisations, in the last years companies have been trying to address this problem by implementing Business Intelligence Systems. Part of the reason for this choice relies in the capabilities of BI systems and tools in managing vast amount of data and extracting insights (Hong et al. 2006; Watson et al. 2001). As proof, the growth of the BI in 2017 was about 7.3%, with revenues around $18.3 billion, and the related expectation to reach $22.8 billion by the end of 2020 (Gartner, 2017).

According to Panian (2012) historically, BI evolved at a high pace through different stages, presenting improvements at each one by integrating previous technologies, instead of derogating them, consequently becoming more complete. At first data mining methods and tools were used for reporting purposes, followed by the secondary development of On-Line Analytic Processing (OLAP) of stored data in data warehouses and data marts. The following stages referred to the emergence of balanced scorecards and later to the increasing use of Web Analytics and Web mining (Panian, 2012). The last and most used tools within the BI framework refer to Business dashboards and Mobile Business intelligence, respectively carrying decision making support functions such as root-cause analysis, predictive analysis, segment analysis for the former, and possibilities to enhance decision making process speed and easiness for the latter (Panian, 2012).

In order to fully exploit the BI potential, research over the Adoption, Utilisation and Success of BI systems has increased in the last years (Ain et al. 2019). Recent examples refer to the study of Mudzana, and Maharaj (2015) regarding quality factors as system quality, information quality and service quality, impacting on the success of a BI system. Others such as Davcheva and Benlian (2018) highlighted the role of real time business intelligence and its impact on visual decision making under time pressure.

However, literature and consequently companies have not succeed in exploiting the whole potential of BI tools and systems, and they have been trying to understand the factors which might lead to a full leverage of BI benefits (Ain et al., 2019). According to the research conducted by Ain et al. (2019), out of the three main fields of investigation for BI systems adoption, utilisation, and success (AUS), just two were investigated in depth: organisational perspective and Information System (IS) perspective. The remaining and less investigated factor for Business

Intelligence AUS refers to users' perspective, with specific knowledge gaps which would relate to individual IT competencies, user perceptions and user decision performance (Ain et all., 2019).

With regards, the qualitative study of Aigner (2013) tried to explore the role, advantages and disadvantages of interactivity and visual aspect of business intelligence from the user perspective, though with awareness of main study limitations related to a low number of interviewed participants and their previous accumulated knowledge being IT professionals.

As for decision-making, even if BI systems would be typically addressed to support it, measurements of the same process outcome are missing from BI research (Ain et al., 2012; Popovic et al., 2012). Similarly, the experimental research of Davcheva & Benlian (2018) did not explore the suitable number of visual cues that decision makers might need in a situation of time pressure using real-time BI, and if user's preferences regarding modifications to visualisations might represent and added value or an obstacle in the decision-making process.

Other studies such as the one conducted by Killen et al. (2020), tried to address the role and the impact visualisations in project portfolio management (PPM). However, limitations of the study refer to the lack of research from the cognitive angle, especially the impact and use of cognitive theories in the decision process, specifically for PPM. Lastly, further investigation brought up by Mudzana, and Maharaj (2015) assessed the impact of DeLone and McLean IS success model within a BI framework, even if the implementation of research was geographically limited to one country.

The intended research would enable to verify the findings brought up by the research of Aigner (2013) through a quantitative study about the perceived benefits and limitations of Visual Business Intelligence, and the consequent validation of a model for measuring the influencing factors of Visual BI on the perceived decision making outcome.

In alignment, with consideration of the literature gaps pointed by Killen et al. (2020), Davcheva and Benlian (2018) and Ain et al. (2019), the study academically contributes respectively to further expanding the knowledge about the influence of business intelligence visual tools systems on decision making considering the cognitive aspect and the point of view of the user. Moreover, in alignment to the contributions brought by Mudzana, and Maharaj (2015), the intended research might enrich the information system literature with the implementation of the tested constructs measurements of the DeLone and McLean model without any geographical limitations regarding the study context.

The intended study will address the role and impact of business intelligence systems and tools on the decision-making perceived success from the standing point of the final users.

The research structure will develop as follows: in the next section (2.) the basic theoretical framework will be discussed, in the following section (3.) the constructs and related hypotheses to validate the model will be explained. The last sections will give a clarification about the methodological approach (4.), the expected contributions (5.), the chapters overview (6.), the workplan (7.) and finally references (8.).

2. Theoretical Framing

2.1 Business Intelligence systems and functions

The meaning of Business Intelligence refer to a set of techniques, tools and processes that support a more effective and faster decision making within business environment, enabling the transformation of data into strategic knowledge and insights for taking business decisions (Sabanovic, & Søilen, 2012; Popovič et al., 2012). On regards, BI systems resemble the previous Decision Support System concept, as they increase the user categories and support a wider variety of decisions (Clark, Jones & Armstrong, 2007). According to Fourati-Jamoussi and Niamba (2016) and Søilen (2015), Business Intelligence (BI) systems find their main purpose in providing tools which can effectively support organisational internal and external processes through different functions.

In the context of current practice the terms "Business Intelligence" (BI) and "Business Analytics" (BA) are addressed interchangeably, though with a distinction: the former refers to a definition given by IT professionals, while the latter result highly used by business community members (Chen et al., 2012; Sircar, 2009; Wixom et al., 2011). Within this framework, general BI processes and sub-processes encompass data gathering, data storage, data analysis, data presentation and delivery (Zheng, Zhang & Li, 2014). Specifically, the literature identifies four main BI systems to enhance the decision-making process: reporting, analysis, monitoring and prediction tools (Sabanovic, 2008).

With regards, the BI reporting function relates to the development on business reports containing intelligence and insights on what has happened during a specific time frame. BI analysis system on the other side focuses on the reasons why a certain situation or process happened, resulting critical as the lonely provision of data without an analysis function would be meaningless (Vesset & McDonough, 2007). Lastly the remaining business intelligence systems are respectively monitoring tools, which enables organisations to control information and data in real time (Sabanovic & Søilen, 2012), and prediction business tools. These last tools aid companies willing to predict what could happen to their business thanks to the use of the data they possess regarding business trends (Vesset & McDonough, 2007).

Examples of BI tools in terms of analysis refer to visualisation tools, which can be described as software accepting and converting raw data to create visualisation that can be understood by managers (Negash & Gray, 2008) while on the other hand dashboards, key performance indicators (KPIs) and business performance management are addressed as monitoring tools, which help controlling data and information in real time Sabanovic & Søilen, 2012).

2.2 Visual Business Intelligence

Among the different tools mentioned in the section above (2.1), dashboard and reporting software represent a part of what in literature is called Visual Business Intelligence (Aigner, 2013). Visual BI, or generally referred to as Data Visualisation (DV), refers to the application of Information Visualisation (InfoVis) within the BI context, in order to graphically reproduce and analyse business data, helping the final users to give a sense to large data sets using a visual perspective (Aigner, 2013; Baltzan, 2014; Iliinsky & Steele 2011; Rodeh et al., 2013). In fact, through the use of human perceptual system, which is effective in elaborating visual cues and inputs, visualisations would enable the users to navigate complex information amounts, or to highlight data patterns or relationships (Aigner, 2013).

The qualitative research of Aigner (2013), based on IT professionals interviews pointed out that the advantages of Visual BI refer not only to the above mentioned structuring and understanding of large data amounts, but also to possibilities for easier comparisons, the highlighting of relationships, changes, trends, time saving and increase of work attractiveness. However, at the same time there might be information distortion, lack of fit between visualisation and task or focus more on gamification and aesthetic rather than content.

With regards, due to the intrinsic nature and functions of BI systems, the interest of managers and executives about their adoption, utilisation and success (AUS) and the related research increased exponentially over the last decades (Ain et al., 2019). Among all the studies that tried to address the different perspectives and hidden value of BI systems, theories such as the DeLone and McLean Information Systems Model (Ain et al., 2019; Mudzana, and Maharaj, 2015), the Cognitive Load Theory (Dacvheva & Benlian, 2018) and the Decision-Making theory (Dacvheva & Benlian, 2018; Killen et al., 2020) have never been used simultaneously, therefore it is the intention of this research to test quantitatively the study findings of Aigner (2013), through the use of all the mentioned theories.

2.3 DeLone and McLean Information System (IS) Success model

According to the studies of Ain et al. (2019) within the research framework for BI systems AUS, the DeLone and McLean's IS success model results to be the main cited and implemented model to investigate different aspects. The model contains six IS success dimensions: information quality, service quality, system quality, use, user satisfaction and net benefits (DeLone & McLean, 1992; DeLone & McLean, 2003). These constructs result complete, as they address the entire information flow spectrum starting by the original source, to the use and lastly the effect on individual and organisational performance (Ain et al., 2019).

For instance, the model has been implemented to identify success measure within BI context, highlighting the dependency of user satisfaction on system quality factors, namely data locatability, data quality and system throughput (Shin, 2003). Other investigations as the one of Mudzana and Maharaj (2015) studied how factors such as system quality, information quality and service quality impact on BI system success.

Moreover, the updated DeLone and McLean (2003) model has been used in empirical studies in different fields of investigation, such as the analysis of a student information system success using student users (Rai, Lang & Welker, 2002), tourism websites (Stockdale & Borovicka 2006; Wang & Liao 2008), systems of knowledge management (Wu & Wang 2006), e-government systems (Hussein, Abdul Karim & Selamat 2007), online learning systems (Lin, 2007), systems for e-commerce (Wang & Liao 2008), decision making quality (Wieder & Ossimitz, 2015), healthcare information system (Gaardboe, & Nyvang, 2017) and data warehousing (Wixom & Watson, 2017).

2.4 Cognitive Load Theory

The Cognitive Load Theory (CLT) was firstly introduced at the end of the 1980's, with the intent of proposing the best method to enhance the absorption of new information thanks to a suitable presentation format for the specific purpose (Merriënboer and Sweller, 2005). According to Paas, Renkl and Sweller (2004) cognitive load refers to the simultaneous mental activity realised using working memory. The theoretical foundations are based on assumptions regarding long-term and working memory mechanism within human cognitive architecture. Precisely, the Cognitive Load Theory supposes that any kind of new information is initially captured and elaborated by working memory, which has limitations regarding capacity and duration, for then being assimilated within the unlimited long-term memory (Anmarkrud et al., 2019; Sweller, Merriënboer & Paas, 2019).

Within this context, literature identifies three types of cognitive load, extraneous, intrinsic and germane. With regards, extraneous, intrinsic and germane cognitive load respectively refers to the format in which information is presented, the type of task that needs to be completed based on the provided information and lastly the necessary resources to assimilate long term knowledge (Merriënboer and Sweller, 2005). In accordance with the studies of Paas et al. (2003), the reduction of extraneous cognitive load through an appropriate presentation format will enable more cognitive resources of any individual to sustain and manage intrinsic and germane load, consequently allowing a better assimilation, analysis and deduction of conclusions of the information presented.

Cognitive Load theory has already been used in certain studies within the Business Intelligence framework, to research how users process visual stimuli and are influenced in their decisions. For instance, the study of Davcheva and Benlian (2018) highlighted that reduction of visual cues present in a real-time BI context decreases cognitive load and enhance decision precision, user certainty within a lower time frame than in other situations.

The rationale refers to the mechanism for which when any user looks at a visualisation, visual information or cues are immediately elaborated by sensory memory, and then just the most relevant information is passed to working memory (Huang, Eades and Hong, 2009). However, a visualisation with too many hints might represent an overload for working memory, with the potential consequence of poor performance, as the more elements have to be processed, most likely one of them will not be noticed or will be forgotten (Merriënboer and Sweller, 2005). According to Huang, Eades and Hong (2009), users working with graphs may encounter difficulties in tracing patterns, relationships and other interactions once cognitive load increases due to the increased graph visual complexity.

At the same time, other researches pointed out that structures such as the visual internet monitoring system enhances accuracy and time of reaction of end users through reduction of visual data displayed (Yelizarov & Gamayunov, 2014).

2.5 Decision Making Theory

Within the framework of Business Intelligence, the various definitions of this kind of systems clearly highlight the supporting function within decision making, as they provide strategic information and knowledge to evaluate the different courses of action to take. The rationale refers to the possibility that BI systems give to users to access information in timely manner, to conduct an analysis and intuitively and effectively provide it (Popovic et al. 2012). As Pourshahid, Richards, and Amyot (2011) highlight, in the last 30 years Business Intelligence tools enabled managers to achieved improved decisions thanks to enhanced organisation of information, data quality and information delivery.

According to Arnott et al. (2017), in order to investigate the patterns of BI system use, nowadays human decision-making theories from behavioural economics appear to be dominantly implemented. On regards the dual process theory of decision-making would result the most relevant, with its theoretical foundations referring to the existence of two cognitive systems within and between which decision making occurs (Arnott et al., 2017), namely System 1 and System 2 (Stanovich & West, 2000).

Specifically, System 1 results to be intuitive and effortless, and the first system to be used when facing a decision, having its roots from instinct behaviour, while System 2 results to be slow, and relying on cognitive effort (Stanovich & West, 2000). Moreover, when considering management decision-making System 1 might lead to better results compared to System 2 (Evans, 2003; Klein et al. 2010; Reyna, 2004) especially for implementing difficult and strategic tasks, though decision makers conception of the same tasks might be more ephemeral (Das & Teng, 1999). On the other side System 2 managerial tasks would be more prone to be stable in nature (Arnott et al., 2017). For these reasons Arnott et all. (2017) suggests that the awareness of when shifting from System 1 intuitive thinking to System 2 rule-based reasoning might be difficult to grasp for either managers and analysts, being influenced as well by context, skills and experience of the decision maker.

On regards, studies conduct by Vessey (1991) reveal that better decision making emerges when decision support tools directly help the decision task, in accordance to notion of cognitive fit, a phenomenon which appears within BI decision-making context when there is the existence of a suitable match between the BI tool data presentation format and the use the same data.

In fact an effective BI system should improve business decision by enhancing final users' abilities to take better courses of action (Bačić & Fadlalla, 2016) especially thanks the role of fundamental elements such as visualisations (Cleveland, 1994; Kosslyn, 1989; Tufte, 1983; Tufte, 1990). Accordingly, additional research within behavioural decision making has proven that decision makers benefit more from information when it is displayed in an explicit format (Pourshahid, Richards, and Amyot 2011). In alignment studies on cognitive fit and bounded rationality propose the potential improvement for the decision making process with the visualisations use, thanks to the elicitation of perception skills, cognitive capabilities, enabling manager to give a proper sense of the provided data (Ware, 2012; Tergan & Keller, 2005).

Visualisation value would be proven as well in practice by the reliance of different organisations on these tools for decision support and business intelligence (Alazmi & Alazmi, 2012). For instance Visual BI tools and technologies would be supporting through interactivity and exploration features Fluid Reasoning, or the recognition ability of patterns (Cavanaugh & Blanchard-Fields, 2006), difficult ability to achieve without the support of any BI system (Bačić & Fadlalla, 2013).

Recent findings specify that visualisations allow users to cope with the limitations of the human working memory and the related limited amount of information it can process, and therefore support decision making with the consideration of large data sets (Killen et al., 2020). For instance, Davcheva & Benlian (2018) explored and prove the positive relationship between more simplified visualisations and the increase in decision-making accuracy; similarly the research of Killen, Geraldi, and Kock (2020) highlighted the benefits of visualisations for project portfolio management decision making.

3. Research Hypotheses

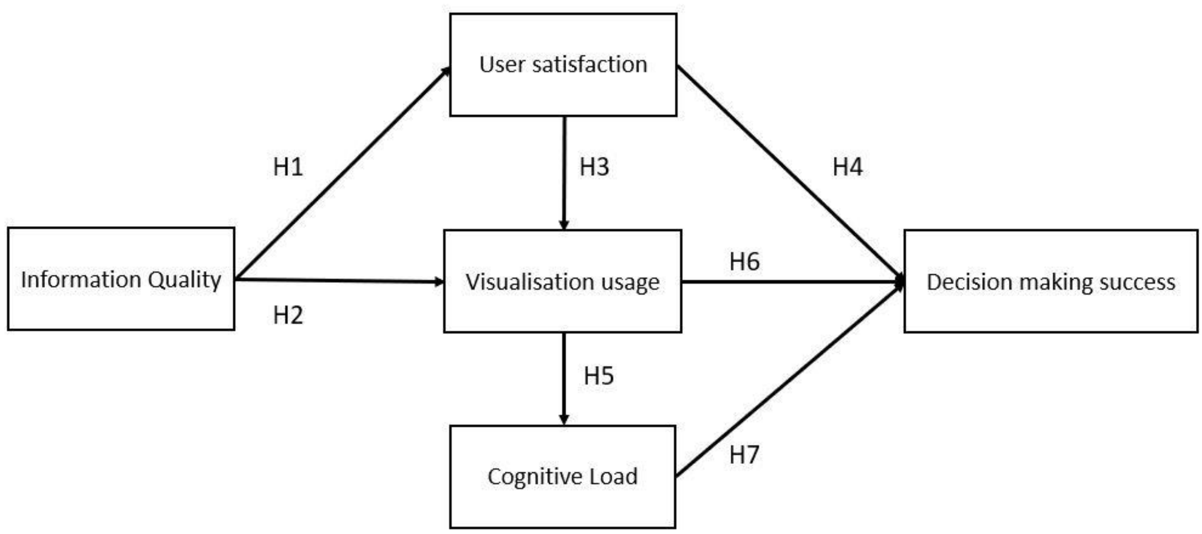
3.1 Constructs

Based on the theoretical background provided in section (2.) and the proposed literature review within section (1.), the constructs of Information Quality, Cognitive Load, User Satisfaction, Visualisation usage and Decision-Making success as outcome variable, are used in order to develop and validate an empirical quantitative model and the related hypotheses.

3.2 Research Model

Figure 1

Research Model



3.3 Decision Making Success

Decision making can be overall described as a process leading to a choice of a preferred option or course of action from a range of alternatives, depending on given requirements or strategies (Wang et al., 2004; Wilson & Keil, 2001). Moreover, decision making is defined as one of the 37 major cognitive processes included in the layered reference model of the brain (Wang et al., 2004; Wang, 2007). With regards, as outcome variable of the research model, the decision making success refers to the perception of the decision makers upon their actions, with measurements adapted from Killen et al. (2020) and referring to outcome based dimensions such as information understandability, expected success, and process oriented dimensions such as process effectiveness.

3.4 Information Quality

According to Petter, DeLone and McLean (2008), the notion of information quality regards the features of the produced information by the business intelligence system (BIS). With regards there is support from literature of the positive relationship between information quality and system use, and between information quality and user satisfaction (Halawi, McCarthy & Aronson 2007; Kositanurit, Ngwenyama & Osei-Bryson Kweku 2006; Livari 2005; Rai et al. 2002). Moreover, an investigation conducted by Mudzana and Maharaj (2015), in order to measure BIS in South Africa using the DeLone and McLean model, further confirms the positive influence of information quality on system use and user satisfaction. Based on the mentioned study contributions, the following hypotheses are formulated:

H1: Information Quality has a positive influence on User Satisfaction

H2: Information Quality has a positive Influence on Visualisation Usage

3.5 User satisfaction

Within the IS context, user satisfaction refers to sensation of pleasure or displeasure stemming from the overall benefits that the user expects to receive from the interaction with the information system. Particularly, every individual owns a set of expected benefits towards the IS, and the degree up to which the system is able to satisfy those expectations is the degree of satisfaction of the user (Seddon, 1997).

On regards, the research of Mudzana and Maharaj (2015), did not highlight a significant positive influence of user satisfaction on business intelligence system use in general, similarly to other studies (Ang & Soh 1997; Vlahos & Ferratt 1995) which were not able to show a direct influence. However, studies such as the one of Hou (2012) pointed out a strong positive influence of end user computing satisfaction on BI system usage, leading to an increase of this las one, confirming at the same time the positive bidirectional influence of DeLone and McLean (2003). Accordingly, Bhokhari's (2005) meta-analysis would provide further confirmation of a positive relationship between user satisfaction and system use within the IS framework.

In addition, within the framework of IS theory, Mudzana and Maharaj (2015) also pointed out the positive relationship between user satisfaction and net benefits, consistently with the findings of Gelderman (1998), Law and Ngai (2007) and Hou (2012). The rationale would refer to the fact that user satisfaction as measure for IS success is justified by better performances of satisfied users than dissatisfied ones, due to the IS effectiveness (Gatian, 1994). On regards, the research of Gatian (1994) would focus on the beneficial impact of user satisfaction about information quality and decision performance, highlighting information effectiveness provided by the Information System and enhanced data processing, report generation and distribution timeliness. Therefore, in accordance to rational thinking the following hypotheses are formulated:

H3: User satisfaction has a positive influence on Visualisation Usage

H4: User Satisfaction has a positive Influence on Decision Making Success

3.6 Visualisation Usage

The concept of visualisation usage is described by Killen et al. (2020) as the degree up to which visualisation are considered and used in a range of portfolio tasks. With regards, the similar but more inclusive concept of system usage in IS theory refers to the degree up to which individuals integrate information systems and the related technologies in completing their tasks and work routine (Goodhue and Thompson, 1995). System usage or use has had a fundamental role within IS research (Barkin & Dickson, 1977; Bokhari, 2005; Schwarz & Chin, 2007), with investigation in academic domains (Burton-Jones & Straub), such as IS success (DeLone & McLean, 1992; Goodhue, 1995) and IS for decision making (Barkin & Dickson, 1977; Yuthas & Young, 1998).

As for this last aspect, the research of Killen et al. (2020) considers visualisations as another tool with the function of reducing decision complexity, consequently leading to improved decision making for any kind of user. In fact, visualisations reduce the cognitive load coming from information elaboration, helping users in recalling or memorising information thanks to the perceivable image they can see (Borkin et al., 2013). Moreover, they would present visual cues capturing people concentration enabling them to focus on area of interest or difference. This mechanism would enable decision makers to exploit human natural/spatial abilities to understand where additional investigation might be necessary (Tegarden, 1999).

Accordingly, the above mentioned findings of Davcheva and Benlian (2018) within the context of real time business intelligence, point out that enhanced visualisation quality through the reduction of complex visual cues would lead to decrease of cognitive load and to improved decision accuracy and time reduction. The findings result to be in alignment with three key visualisation mechanisms namely the effective tool to understand and manage large quantities of multi-dimensional data (Tufte, 2001), the increase the capacity of working memory (Ware, 2012) and its duration (MacNeice, 1961). Thus, according to the above discussion:

H5: Visualisation Usage has a positive influence on Cognitive Load

H6: Visualisation Usage has a positive influence on Decision Making Success

3.7 Cognitive Load

Cognitive Load refers simultaneous implementation of mental activity through the use of working memory (Paas, Renkl & Sweller, 2004). Studies of Merriënboer and Sweller (2005) identifies three types of cognitive load, extraneous, intrinsic and germane. In alignment, the recent findings of Davcheva & Benlian, (2018) points out that an adequate visualisation during the decision-making process would enable more cognitive resources for a user to address intrinsic and germane load. Therefore, the increased spare additional cognition capacities would help the individual to assess and draw conclusion from the information presented.

Moreover, other finding in the economics (Deck, & Jahedi, 2015) , medicine (Burgess, 2009) and personal interaction (Gilbert, & Osborne, 1989) fields showed that a high cognitive load has been associated with poor decision-making performance (Davcheva & Benlian, 2018). Similarly, other researches pointed out the negative influence that information overload has on decision making (Davis and Ganeshan, 2009; Roetzel, 2015). Consequently, the following hypothesis is formulated:

H7: Cognitive Load has a negative Influence on Decision Making Success

3.8. Literature

Here as follows, a literature table is presented, containing some of the most relevant articles which enabled the previous reasonings and hypotheses formulation. The sources refer to different kind of studies, though in the common research fields of this investigation regarding BI, Visual Analytics, Cognition, Information Visualisation and Decision Making.

3.8.1 Literature table

Table 1

Literature table

Title	**Reference**	**Design**	**Content**
"Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review"	(2019) NoorUl Ain, Giovanni Vaia, William H. DeLone, Mehwish Waheed	Literature review	The article explores the difficulties and challenges regarding the adoption, utilisation, and success of BI systems through a literature review of ll the previous studies. It highlights theories and factors employed to address BI investigations, the related issues and it points research gaps that might have not been covered, therefore leaving possibilities for future research.
"Visual Decision-Making in Real-Time Business Intelligence: A Social Media Marketing Example"	(2018) Davcheva, E., & Benlian, A.	Experimental study	The research sheds light on the use of visualisations in real-time BI. The results of the experiment show that a reduction of visualisation s complexity leads to reduced cognitive load, enhancing at the same time decision making performance, specifically in situations limited time and high-speed data.
"The role of decision makers' use of visualizations in project portfolio decision making"	(2020) Killen, C. P., Geraldi, J., & Kock, A	Quantitative study	The study investigates the role and influence of visualisation in the decision-making process within a project portfolio context. Data were collected through a questionnaire and they highlighted a positive correlation between use of visualisation and decision making leading to the outcome of portfolio success.
"Measuring the success of business-intelligence systems in South Africa: an empirical investigation applying the DeLone and McLean model"	(2015) Mudzana, T., Maharaj, M	Quantitative study	The aim of the study results to be the identification of post implementation factors contributing to the Business Intelligence System in south African organisations. Data were collected through a questionnaire, and the majority of results was in alignment with the original propositions of the DeLone and McLean model for IS success.
"An examination of the impact of business intelligence systems on organizational decision making and performance: The case of France"	(2017) Gauzelin, S., & Bentz, H.	Qualitative study	The investigation addresses BI systems impact on organisational decision making and performance, within a SMEs context. Data collected through interviews show that BI facilitates decision making, improves efficiency of the company enabling it last one to satisfy customer needs and to increase employees' satisfaction.

"Current Work Practice and Users' Perspectives on Visualization and Interactivity in Business Intelligence"	(2013), Aigner, W.	Qualitative study	The article tries to uncover the current work practices and the user perspective regarding the implementation of information visualisations and visual Business Intelligence. Insights gathered through interviews highlight that visualisation are not used enough, probably due to their advancement in technology and to habit of their users, used to work with symbols. Reasons for this last aspect refer to unawareness of users about visual possibilities, which might help them according to the interview subjects. Need for a larger qualitative or quantitative study is mentioned.
"Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: An empirical study of Taiwan's electronics industry"	(2012), Hou, CK.	Quantitative study	The research addresses the nature of the relationship between end-user computing satisfaction (EUCS), system usage, and individual performance. The results coming from the data analysis points out a positive relationship between EUCS and system use and individual performance, consistently to the DeLone and McLean's model.
"Interactive data visualisation for accounting information: a three-fit perspective"	(2018), Perdana, A., Robb, A., Rohde, F.	Experimental study	The authors investigate the appropriateness of interactive data visualisations for non-professional investors while accessing accounting information. Results suggest that ID visualisations moderate non-professional investors cognitive effort, enabling them to complete a wide range of simple and multipart tasks.
"The DeLone and McLean Model of Information Systems Success: A Ten-Year Update"	(2003) DeLone, W., McLean, E. R.	Literature review, study case	The article discusses all the contributions that have bene made to the model presented by the same authors and present an updated version upon the received critics and suggestions, listing six main factors contributing to an IS success. Then, the model is appleade to a e-commerce study case in order to show its functioning.
"Is user satisfaction a valid measure of system effectiveness?"	(1994), Gatian, A., W.	Quantitative study	The author tries to further explore the relationship between user satisfaction and user behaviour such as enhanced productivity, decision making within an IS context. Data gathered through a questionnaire validate the pre-existent relationship, or the positive influence of user satisfaction on user behaviour.

4. Methodology

4.1 Research design, context

The research will take the shape of quantitative study, due to the expressed need to address the role of Visual BI tools using a quantitative method (Aigner, 2013) and to the exclusion or lack of consideration in previous investigations (e.g. cognitive load) of some of the constructs present in the research model in previous investigations. On regards, in order to validate the quantitative research model, data will be collected by means of an online self-administered questionnaire, because of reasons related to costs, time and difficulty in reaching the target sample. The first part of the questionnaire will be represented by five-point Likert-scale and confirmatory questions with the purpose of assessing the five factors of the proposed research model. The final part will include demographic questions such as age, gender, role and industry. The online questionnaire will be developed from the prior studies mentioned in the section (2.) and adapted to suit the BI context and the related visual tools.

4.2 Sample description

The intended target mainly refers to any type of professional, manager, or employee who uses BI tools monthly, if not weekly, to perform or support their functions and to make decisions, regardless pre-existing IT, IS or BI knowledge.

4.3 Data collection context and procedure

The research will be implemented mostly online, specifically through working professional social media such as LinkedIn, where the questionnaire will be shared and fulfilled by participants belonging to on topic groups (ex. BI professionals' groups, visual analytics). Incentives to participate in the study will be composed of a report presenting the main findings of the research that will be delivered to participants at the end.

4.4 Measures and data analysis

The constructs will be measured through items adapted from previous studies (4.5 Items table) which addressed the constructs or similar ones through Likert scales, while the analysis of the gathered data will be implemented through a Structural Equation Modelling. The missing values will be handled observing Grimm and Wagner's (2020) recommendations to optimize the accuracy of the estimations obtained in the SEM calculations using Smart PLS.

<u>4.5 Items table</u>

Table 2

Items table

Items	Reference	Original Items	Adapted Items
Information Quality	(1988) Doll, W., J., Torkzadeh, G.	• Does the system provide the precise information you need? • Does the information content meet your needs? • Does the system provide reports that seem to be just about exactly what you need? • Does the system provide sufficient information? • Do you find the output relevant?	• The visualisation system provides the information I need. • The information content meets my needs • The visual system provides insights that correspond to what I need • The visual system provides sufficient information • I find the visualisation output relevant
User Satisfaction	(2015) Mudzana, T., Maharaj, M	• Meets information needs • I think the system is very helpful • Overall, I am satisfied with the system	• The visualisation system meets my information needs • I think the visualisation system is very helpful • Overall, I am satisfied with the visualisation system
Visualisation Usage	(2015) Mudzana, T., Maharaj, M	• I frequently use the system • I depend upon the system • I only use the system when it is absolutely necessary for completing a specific task	• I frequently use the visualisation system and tools • I depend upon the system • I only use visualisations when it is absolutely necessary for completing a specific task
Cognitive Load	(2017) Klepsch, M., Schmitz, F., & Seufert, T.	• For this task, many things needed to be kept in mind simultaneously • This task was very complex • For this task, I had to highly engage myself • For this task, I had to think intensively what things meant • During this task, it was exhausting to find the important information • The design of this task was very convenient for learning • During this task, it was difficult to recognize and link the crucial information	• For my work-related tasks, many things need to be kept in mind simultaneously • My work-related tasks are very complex • For my work-related tasks I have to highly engage myself • For my work-related tasks, I have to think intensively what things mean • While carrying out my work-related tasks it is exhausting to find the important information • The design of my work-related tasks is very inconvenient for working well • During my work-related tasks, it is difficult to recognize and link the crucial information
Decision Making success	(2020) Killen, C. P., Geraldi, J., & Kock, A	• In general, our portfolio decision-making process is working well. • I am confident that decision makers/we understand the project portfolio information when making decisions. • Generally, the portfolio decision makers make successful decisions • Overall, we execute our project portfolio management process in a well-structured way	• In general, my/our decision-making progress works well • I am confident in understanding the provided information when making decisions • Generally, company decision makers/we make successful decisions • Overall, we execute our job-related tasks/process in a well-structured way

5. Contributions

In alignment to the reasons for study relevance mentioned in the above section (1.2) the intended research might academically contribute to the literature by validating the qualitative findings of Aigner (2013) through a quantitative study implemented thanks to the proposed research model. Moreover, the study might contribute to IS literature with the application of some Mudzana and Maharaj (2015) constructs and relative measurements of the DeLone and McLean model outside the only South African context. As for the gaps brought by Killen et al. (2020), Davcheva and Benlian (2018) and Ain et al. (2019) the research proposes a theoretical framework which would investigate and enrich the knowledge regarding the role and impact of Visual BI from the user perspective on the decision-making process, and with the consideration of the cognitive aspect.

Moreover, practical contributions would refer to the provision for any sort of professional, manager, employee and organisation using BI tools, to comprehend which elements need higher consideration in order to leverage the BIS potential. At the same time developers and final sellers might be able to understand more suitable concept for the design of BIS functionalities and features. Lastly, social contribution would be found indirectly, as consequence of enhanced organisational performance thanks to a better understanding of BI potential. This outcome might enable companies to better understand their internal and external actions, with the final consequence of achieving better fit between products or services and consumers.

6. Chapter overview

Abstract
List of Abbreviations
List of Figures
List of Tables
1.Introduction
2.Problem Statement and Purpose of the Research
3.Theoretical Framework
- 3.1 Business Intelligence systems and functions
- 3.2 Visual Business Intelligence
- 3.3 DeLone and McLean Information Systems (IS) Success model
- 3.4 Cognitive Load Theory
- 3.5 Decision Making Theory

4.Research Model and Research Hypotheses
5.Review of Literature
6.Research Model and Hypotheses Review
7.Methodology
8.Data Analysis
9.Research Findings
10. Contributions
11.Discussion & Limitations
Bibliography
Appendix

7. Workplan

Table 3

Workplan

Time Period	Activity	Status
01.09 – 30.09	Exposé research and writing	Completed
30.09	Exposé submission	Completed
05.10 – 20.10	Questionnaire design	To follow
20.10 – 31.10	Questionnaire testing and improvements	To follow
01.11 – 21.11	Data collection	To follow
22.11 – 07.12	Data Analysis	To follow
08.12 – 10.01	Thesis writing and review	To follow
13.01	Thesis submission	To follow
08.01 – 19.01	Thesis presentation design	To follow
19.01	Thesis presentation submission	To follow

8. References

Aigner, W. (2013). Current Work Practice and Users' Perspectives on Visualization and Interactivity in Business Intelligence. 2013 17th International Conference on Information Visualisation.

Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review. *Decision Support Systems*, 125, 1–13.

Ang, J., & Soh, P. (1997). User information satisfaction, job satisfaction and computer background: An exploratory study. Information & Management, 32(5), 255-266.

Anmarkrud, Ø, Andresen, A., & Bråten, I. (2019). Cognitive Load and Working Memory in Multimedia Learning: Conceptual and Measurement Issues. Educational Psychologist, 54(2), 61-83.

Alazmi, A. R. R., & Alazmi, A. A. R. (2012). Data mining and visualization of large databases. International Journal of Computer Science and Security, 6(5), 295-314

Arnott, D., Lizama, F., & Song, Y. (2017). Patterns of business intelligence systems use in organizations. Decision Support Systems, 97, 58–68.

Bačić, D., & Fadlalla, A. (2013). Business Information Visualization: A Visual Intelligence-Based Framework, AMCIS 2013, Chicago, IL, 1-9.

Bačić, D., & Fadlalla, A. (2016). Business information visualization intellectual contributions: An integrative framework of visualization capabilities and dimensions of visual intelligence. Decision Support Systems, 89, 77–86.

Baltzan, P. (2014). Business Driven Information Systems (4th ed.). McGraw-Hill Education.

Barkin, S. R., & Dickson, G. W. (1977). An investigation of information system utilization. Information & Management, 1(1), 35–45.

Bokhari, R. H. (2005). The relationship between system usage and user satisfaction: a meta-analysis. Journal of Enterprise Information Management, 18(2), 211–234.

Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., & Pfister, H. (2013). What Makes a Visualization Memorable? IEEE Transactions on Visualization and Computer Graphics, 19(12), 2306–2315.

Burgess, D. J. (2009). Are Providers More Likely to Contribute to Healthcare Disparities Under High Levels of Cognitive Load? How Features of the Healthcare Setting May Lead to Biases in Medical Decision Making. Medical Decision Making, 30(2), 246–257.

Burton-Jones, A., & Straub, D. W. (2006). Reconceptualizing System Usage: An Approach and Empirical Test. Information Systems Research, 17(3), 228–246.

Cavanaugh, J. C., & Blanchard-Fields, F. (2006). Adult development and aging. Belmont, CA: Wadsworth, Thomson Learning.

Chen, Chiang, & Storey. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165.

Clark, T. D., Jones, M. C., & Armstrong, C. P. (2007). The Dynamic Structure of Management Support Systems: Theory Development, Research Focus, and Direction. MIS Quarterly, 31(3), 579.

Cleveland, W. S. (1994). The Elements of Graphing Data (2nd ed.). Hobart Press.

Das, T. K., & Teng, B.-S. (1999). Cognitive Biases and Strategic Decision Processes: An Integrative Perspective. Journal of Management Studies, 36(6), 757–778.

Davcheva, E., & Benlian, A. (2018). Visual Decision-Making in Real-Time Business Intelligence: A Social Media Marketing Example. *Proceedings of the 51st Hawaii International Conference on System Sciences*.

Davis, J. G., & Ganeshan, S. (2009). Aversion to Loss and Information Overload: An Experimental Investigation. Proceedings of International Conference on Information Systems, 1–14.

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. European Economic Review, 78, 97–119.

DeLone W. H., McLean, E. R. Information systems success: the quest for the dependent variable, Information Systems Research 3 (1) (1992) 60–95.

DeLone W. H., McLean, E. R. The DeLone and McLean model of information systems success: a ten-year update, Journal of Management Information Systems 19 (4) (2003) 9–30

Evans, J. S. (2003). In two minds: dual-process accounts of reasoning. Trends in Cognitive Sciences, 7(10), 454–459.

Fourati-Jamoussi, F. & Niamba, C.N. (2016). An evaluation of business intelligence tools: a cluster analysis of users' perceptions. Journal of Intelligence Studies in Business, 6(1), 37- 47.

Gaardboe, R., Nyvang, T., & Sandalgaard, N. (2017). Business Intelligence Success applied to Healthcare Information Systems. Procedia Computer Science, 121, 483-490.

Gartner, Business Intelligence and Analytics Trends in, (2017).

Gatian, A. W. (1994). Is user satisfaction a valid measure of system effectiveness? Information & Management, 26(3), 119–131.

Gauzelin, S., & Bentz, H. (2017). An examination of the impact of business intelligence systems on organizational decision making and performance: The case of France. Journal of Intelligence Studies in Business, 7(2).

Gelderman, M. (1998). The relation between user satisfaction, usage of information systems and performance. Information & Management, 34(1), 11–18.

Gilbert, D. T., & Osborne, R. E. (1989). Thinking backward: Some curable and incurable consequences of cognitive busyness. Journal of Personality and Social Psychology, 57(6), 940–949.

Goodhue, D. L. (1995). Understanding User Evaluations of Information Systems. Management Science, 41(12), 1827–1844.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. MIS Quarterly, 19(2), 213.

Grimm, M. S., & Wagner, R. (2020). The Impact of Missing Values on PLS, ML and FIML Model Fit. Archives of Data Science, Series A, 6(1), 04.

Halawi, L.A., McCarthy, R.V. & Aronson, J.E., (2007). An empirical investigation of knowledge management systems' success', Journal of Computer Information Systems 48(2), 121–135.

Hong, S., Katerattanakul, P., Hong, S., & Cao, Q. (2006). Usage And Perceived Impact Of Data Warehouses: A Study In Korean Financial Companies. International Journal of Information Technology & Decision Making, 05(02), 297-315.

Hou, C.-K. (2012). Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: An empirical study of Taiwan's electronics industry. International Journal of Information Management, 32(6), 560–573.

Huang, W., Eades, P., & Hong, S. (2009). Measuring Effectiveness of Graph Visualizations: A Cognitive Load Perspective. Information Visualization, 8(3), 139-152.

Hussein, R., Abdul Karim, N. & Selamat, M., (2007), 'The impact of technological factors on information systems success in the electronic-government context', Business Process Management Journal 13(5), 613–627.

Iliinsky, N., & Steele, J. (2011). Designing Data Visualizations: Representing Informational Relationships (1st ed.). O'Reilly Media.

Killen, C. P., Geraldi, J., & Kock, A. (2020). The role of decision makers’ use of visualizations in project portfolio decision making. *International Journal of Project Management*, 38(5), 267–277.

Klein, G., Calderwood, R., & Clinton-Cirocco, A. (2010). Rapid Decision Making on the Fire Ground: The Original Study Plus a Postscript. Journal of Cognitive Engineering and Decision Making, 4(3), 186–209.

Klepsch, M., Schmitz, F., & Seufert, T. (2017). Development and Validation of Two Instruments Measuring Intrinsic, Extraneous, and Germane Cognitive Load. Frontiers in Psychology, 8.

Kositanurit, B., Ngwenyama, O., & Osei-Bryson, K.-M. (2006). An exploration of factors that impact individual performance in an ERP environment: an analysis using multiple analytical techniques. European Journal of Information Systems, 15(6), 556–568.

Kosslyn, S. M. (1989). Understanding charts and graphs. Applied Cognitive Psychology, 3(3), 185–225.

Law, C. C. H., & Ngai, E. W. T. (2007). ERP systems adoption: An exploratory study of the organizational factors and impacts of ERP success. Information & Management, 44(4), 418–432.

Lin, H.F., (2007), Measuring online learning systems success: Applying the updated DeLone and McLean mode. CyberPsychology & Behavior 10(6), 817–820.

MacNeice, H., (1961). Production forecasting, planning, and control. New York, London, NY: John Wiley.

Merriënboer, J. J., & Sweller, J. (2005). Cognitive Load Theory and Complex Learning: Recent Developments and Future Directions. Educational Psychology Review, 17(2), 147-177.

Mudzana, T., Maharaj, M. (2015). Measuring the success of business-intelligence systems in South Africa: an empirical investigation applying the DeLone and McLean model. South African Journal of Information Management 17 (1), 1–7.

Negash, S., & Gray, P. (2008). Business intelligence. Handbook on decision support systems 2, 175-193.

Panian, Z. (2012). The Evolution of Business Intelligence: From Historical Data Mining to Mobile and Locationbased Intelligence. Proceedings of the 4th WSEAS World Multiconference on Applied Economics, Business and Development (AEBD ’12), 118–128.

Paas, F., Renkl, A., & Sweller, J. (2004). Cognitive Load Theory: Instructional Implications of the Interaction between Information Structures and Cognitive Architecture. Instructional Science, 32(1/2), 1-8.

Paas, F., & Sweller, J. (n.d.). Implications of Cognitive Load Theory for Multimedia Learning. The Cambridge Handbook of Multimedia Learning, 27-42.

Paas, F., Tuovinen, J. E., Tabbers, H., & Gerven, P. W. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. Educational Psychologist, 38(1), 63-71.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. Decision Support Systems, 54(1), 729-739.

Pourshahid, A., Richards, G., & Amyot, D. (2011). Toward a Goal-Oriented, Business Intelligence Decision-Making Framework. Lecture Notes in Business Information Processing E-Technologies: Transformation in a Connected World, 100-115.

Rai, A., Lang, S.S. & Welker, R.B., 2002, 'Assessing the validity of IS success models: An empirical test and theoretical analysis', Information Systems Research 13(1), 50–69.

Reyna, V. F. (2004). How People Make Decisions That Involve Risk. Current Directions in Psychological Science, 13(2), 60–66.

Rodeh, O., Helman, H., & Chambliss, D. (2013, October). IBM Research Report: Visualizing Block IO Workloads. IBM Reasearch Division, Almaden Research Center, 650 harry Road, San Jose, CA 95120-6099 USA. https://dominoweb.draco.res.ibm.com/reports/rj10514.pdf

Roetzel, P. G. (2015). The Impact of Creativity and Information Load on Escalation of Commitment. Proceedings of European Conference on Information Systems ECIS., 1–16.

Roetzel, P., & Fehrenbacher, D. (2019). On the Role of Information Overload in Information Systems (IS) Success: Empirical Evidence from Decision Support Systems. Fortieth International Conference on Information Systems (ICIS) (Munich), 1–17.

Sabanovic, A. (2008). Business Intelligence Software Customers' Understanding, Expectations and Needs (Dissertation). Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:hkr:diva-4707

Sabanovic, A., & Søilen, K. S. (2012). Customers' Expectations and Needs in the Business Intelligence Software Market. Journal of Intelligence Studies in Business, 2(1).

Schwarz, A., & Chin, W. (2007). Looking Forward: Toward an Understanding of the Nature and Definition of IT Acceptance. Journal of the Association for Information Systems, 8(4), 230–243.

Seddon, P. B. (1997). A Respecification and Extension of the DeLone and McLean Model of IS Success. Information Systems Research, 8(3), 240-253.

Shin, B., An exploratory investigation of system success factors in data warehousing, Journal of the Association for Information Systems 4 (1) (2003) 6.

Sircar, S. (2009). Business Intelligence in the Business Curriculum. Communications of the Association for Information Systems, 24(17), 289–302.

Søilen, K. S. (2015). A place for intelligence studies as a scientific discipline. Journal of Intelligence Studies in Business, 5(3), 35-46.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? Behavioral and Brain Sciences, 23(5), 645–665.

Stockdale, R. & Borovicka, M., 2006, 'Developing an online business community: A travel industry case study', proceedings of the 39th Annual Hawaii International Conference, Hawaii, 134.

Sweller, J., Merriënboer, J. J., & Paas, F. (2019). Cognitive Architecture and Instructional Design: 20 Years Later. Educational Psychology Review, 31(2), 261-292.

Tegarden, D. P. (1999). Business Information Visualization. Communications of the Association for Information Systems, 1, 1–39.

Tergan, S. & Keller, T. (2005). Knowledge and Information Visualization Searching for Synergies. Berlin, NH: Springer.

Tufte, E. R. (1983). The visual display of quantitative information. Cheshire, CT: Graphics Press.

Tufte, E. R. (1990). Envisioning Information. Cheshire, CT: Graphics Pr.

Tufte, E. R. (2001). The visual display of quantitative information. Cheshire, CT: Graphics Press.

Vesset, D., & McDonough, B. (2007). Worldwide Business Intelligence Tools 2006 Vendor Share. IDC Software Market Forecaster database, 1.

Vessey, I. (1991). Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature. Decision Sciences, 22(2), 219-240.

Vlahos, G. E., & Ferratt, T. W. (1995). Information technology use by managers in Greece to support decision making: Amount, perceived value, and satisfaction. Information & Management, 29(6), 305-315.

Wang, Y., Wang, Y., Patel, S., & Patel, D. (2004). A layered reference model of the brain (LRMB). IEEE Transactions on Systems, Man, and Cybernetics (C), 36(2), 124-133.

Wang, Y. (2007). The Theoretical Framework of Cognitive Informatics. International Journal of Cognitive Informatics and Natural Intelligence, 1(1), 1–27.

Ware, C. (2012). Information Visualization: Perception for Design (Interactive Technologies) (3rd ed.). Morgan Kaufmann.

Watson, H., Ariyachandra, T., & Matyska, R. J. (2001). Data Warehousing Stages of Growth. Information Systems Management, 18(3), 42-50.

Wieder, B., & Ossimitz, M. (2015). The Impact of Business Intelligence on the Quality of Decision Making – A Mediation Model. Procedia Computer Science, 64, 1163-1171.

Wilson, R. A., & Keil, F. C. (2001). The MIT encyclopedia of the cognitive sciences. Cambridge,, MA: The MIT Press.

Wixom, B. H., & Watson, H. J. (2001). An Empirical Investigation of the Factors Affecting Data Warehousing Success. MIS Quarterly, 25(1), 17.

Wixom, B., Ariyachandra, T., Goul, M., Gray, P., Kulkarni, U., & Phillips-Wren, G. (2011). The Current State of Business Intelligence in Academia. Communications of the Association for Information Systems, 29, 299–312.

Wu, J.H. & Wang, Y.M., 2006, ‘Measuring KMS success: A respecification of the DeLone and McLean model’, Information and Management 43(6), 728–739.

Yelizarov, A., & Gamayunov, D. (2014). Adaptive Visualization Interface That Manages User's Cognitive Load Based on Interaction Characteristics. Proceedings of the 7th International Symposium on Visual Information Communication and Interaction - VINCI '14.

Yuthas, K., & Young, S. T. (1998). Material matters: Assessing the effectiveness of materials management IS. Information & Management, 33(3), 115–124.

Zheng, G., Zhang, C., &; Li, L. (2014). Bringing business intelligence to healthcare informatics curriculum. Proceedings of the 45th ACM Technical Symposium on Computer Science Education - SIGCSE '14.

Zheng, J. G. (2017). Data Visualization in Business Intelligence. Global Business Intelligence, 67-81.