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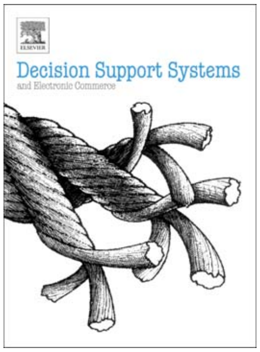

Getting Value from Business Intelligence Systems: A Review and Research Agenda

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Abstract

Much of the research on Business Intelligence (BI) has examined the ability of BI systems to help organizations address challenges and opportunities. However, the literature is fragmented and lacks an overarching framework to integrate findings and systematically guide research. Moreover, researchers and practitioners continue to question the value of BI systems. This study reviews and synthesizes empirical Information System (IS) studies to learn *what we know, how well we know, and what we need to know about the processes of organizations obtaining business value from BI systems.* The study aims to identify which parts of the BI business value process have been studied and are still most in need of research, and to propose specific research questions for the future. The findings show that organizations appear to obtain value from BI systems according to the process suggested by Soh and Markus (1995), as a chain of necessary conditions from BI investments to BI assets to BI impacts to organizational performance; however, researchers have not sufficiently studied the probabilistic processes that link the necessary conditions together. Moreover, the research has not sufficiently covered all relevant levels of analysis, nor examined how the levels link up. Overall, the paper identified many opportunities for researchers to provide a more complete picture of how organizations can and do obtain value from BI.

Keywords: Business intelligence, analytics, big data, data mining, data warehousing, business value

1. Introduction

'Business Intelligence' (BI) has become an increasingly important concept with the availability of 'big data' and advances in machine intelligence [1]. Receiving widespread interest in both academia and industry [2], BI systems are now used extensively in many areas of business that involve making decisions to create value. However, to help BI achieve its full potential, practitioners and researchers need to more fully understand the processes through which organizations can get value from BI. To date, researchers have examined BI using a variety of theories, research lenses, and empirical approaches. While these various streams of study provide diverse views on BI, they can also make it difficult to build a holistic and integrated view of BI business value and sustain a cumulative research tradition. While many authors address rather specific research questions relating to how BI creates business value, no comprehensive research agenda has been developed to understand the process of organizations obtaining business value from BI. Therefore, the research question addressed in this paper is: *What do we know, how well do we know, and what do we need to know about the processes of organizations obtaining business value from BI systems?* The aim of this literature review is to learn the extent to which we can answer this question based on existing literature, identify which parts of the answer are most in need of further research, and reveal key research questions for future work.

Rather than having a well-accepted and specific definition [3], BI is typically used as an 'umbrella' term to describe a process [2], or concepts and methods [4], that improve decision making by using fact-based support systems. Many terms (such *as "business intelligence", "business analytics", "big data", "data mining", and "data warehousing*") are often used interchangeably in the literature, with authors variously describing BI as a "process and a product" [5 p. 121], "a process, a product, and a set of technologies, or a combination of these" [2 p. 87], or a product alone [6]. As a result of these diverse definitions and perspectives, and the growing interest in BI in academia and importance to industry, it is important to synthesize the literature to determine what we already know about the process of generating business value from BI, what we still need to know, and how we can get there. There are a number of studies that contribute, in different ways, to this knowledge. Seddon et al. [6], for example, developed a BI success model but did not expose gaps in the literature or propose future directions. Similarly, while Arnott and Pervan [7] analysed BI studies from 1990-2003, and Jourdan el al. [5] analysed BI studies from 1997-2006, neither paper focused on the process through which BI contributed to business value. Thus, there remains a need for a deeper analysis of the processes of organizations getting value from BI [8].

In keeping with past literature, in this paper the term BI is used to refer to a set of concepts and methods based on fact-based support systems for improving decision making [9], and the term 'BI system' is used to refer to both model-oriented [7] and data-oriented decision support systems [7, 10, 11]. Specifically, BI system here is defined as a system comprised of both technical and organizational elements that presents historical information to its users for analysis, query and reporting, to enable effective decision-making and management support, to increase the performance of business processes. To learn what the research literature can tell us about the processes of organizations obtaining value from BI, the IS business value model of Soh and Markus [12] is used, incorporating constructs suggested by Melville et al. [13] and Schryen [14]. Drawing on BI research published from 1/2000-8/2015, insights are explored in each area of the framework to expose gaps and reveal unexplained or partially unexplained areas in need of further research.

2. Review of Prior Literature: Paper Selection, Framework, and Coding process

In this section, the conduct of the literature review is explained and the framework used to structure the coding is described and illustrated.

2.1. Paper Selection

Fig.1 shows the paper selection process. This review covers BI research published from 1/2000-8/2015. Since there are no clear criteria governing the choice of outlets [15, 16], journals were selected using a two-step approach. First, to survey IS literature, major IS journals (included in the Association for Information Systems' Senior Scholars' Basket of Journals), and the *Decision Support Systems* journal, in which BI research often appears, were included. Because quality BI research could also be published outside these journals, Scopus's citation count was used as a proxy for the relative importance of works published outside the Information Systems' Senior Scholars' Basket of Journals and Decision Support Systems, with the threshold for inclusion set to a minimum of 25 citations as deployed by Tamm et al [17]. Thus, as Table 1 shows, this review focuses on papers in any of nine top IS journals (the Senior Scholars' Basket plus DSS), whether highly cited or not, plus other BI papers cited 25 times or more in Scopus. ProQuest, Ebsco, ScienceDirect, ABI/INFORM, and Wiley-Blackwell Pilot 2015 were used to search for articles; book reviews or editorials were excluded.

To ensure data consistency and relevance across the collection, only publications containing "*business intelligence*", "*business analytics*", "*big data*", "*data mining*" or "*data warehousing*" in their title, abstract, or subject indexing (when applicable) were retrieved. The choice of these keywords was intended to focus the search and analysis on publications of direct relevance. Using the described search criteria within the selected journals and highly cited papers in Scopus for the period of 1/2000-8/2015, 738 articles were collected. Papers whose concepts of BI did not match with the proposed definition such as multidimensional cube algebra [18], or large scale multidimensional data [19], were then excluded along with papers which despite having keywords appearing in the abstracts or subject heading did not investigate BI. This resulted in 184 articles which were then filtered for relevance by analysing the abstracts and skimming the content. Non-empirical studies were excluded,

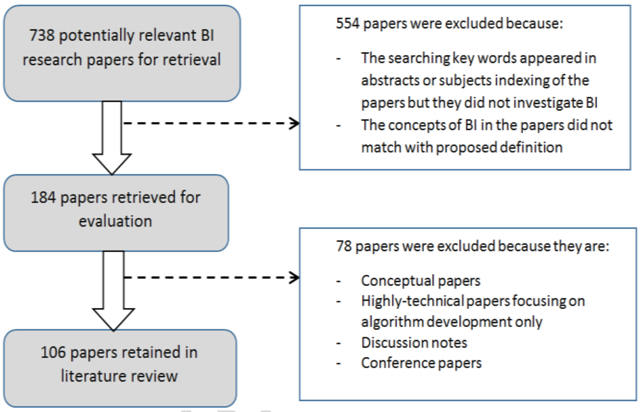

Fig. 1 Diagram of papers selection process

leaving 106 papers which formed the set of articles examined in subsequent sections of this paper.

Table 1
Review process.

Year of Publication	**1/2000-8/2015**
Keywords	"Business intelligence", "Business analytics", "Big data", "Data mining", "Data warehousing"
Journals	• *European Journal of Information Systems (EJIS)* • *Information Systems Journal (ISJ)* • *Information Systems Research (ISR)* • *Journal of Association for Information Systems (JAIS)* • *Journal of Information Technology (JIT)* • *Journal of Management Information Systems (JMIS)* • *Journal of Strategic Information Systems (JSIS)* • *MIS Quarterly (MISQ)* • *Decision Support Systems (DSS)* • *Highly cited papers from other journals (HCP)*
Search engines and databases	ProQuest, Ebsco, ScienceDirect, ABI/INFORM database, Wiley-Blackwell Pilot 2015, Scopus

2.2. BI Business Value Framework

To provide a comprehensive end-to-end view of the processes through which business value is obtained from BI systems, a framework is required to structure the analysis. Fig. 2 presents such a framework. The BI business value framework synthesized herein integrates Soh and Markus's [12], Melville et al.'s [13], and Schryen's [14] models on IS business value. The approach of synthesizing three prominent IS business value models to organize the presentation of prior research "is not an attempt to unify (and simplify) different perspectives applied by researchers, but [rather] to identify and present their shared understanding of IS business value …The advantage of drawing on these research models lies in their wide adoption by IS researchers, which allows us to map and assess the research findings of IS business value literature appropriately…" [14 p. 142]

In line with an explanatory, theory-based review, the proposed framework is then used to structure the presentation of the research findings in the reviewed papers [20]. While there are other ways to model and review the IT business value literature [e.g. 21, 22, 23], the models drawn on here have the advantage of building upon each other, therefore offering a cumulative tradition upon which to build a firm research agenda. These models have also been widely adopted by IS researchers facilitating assessment and mapping of research findings in the BI business value literature.

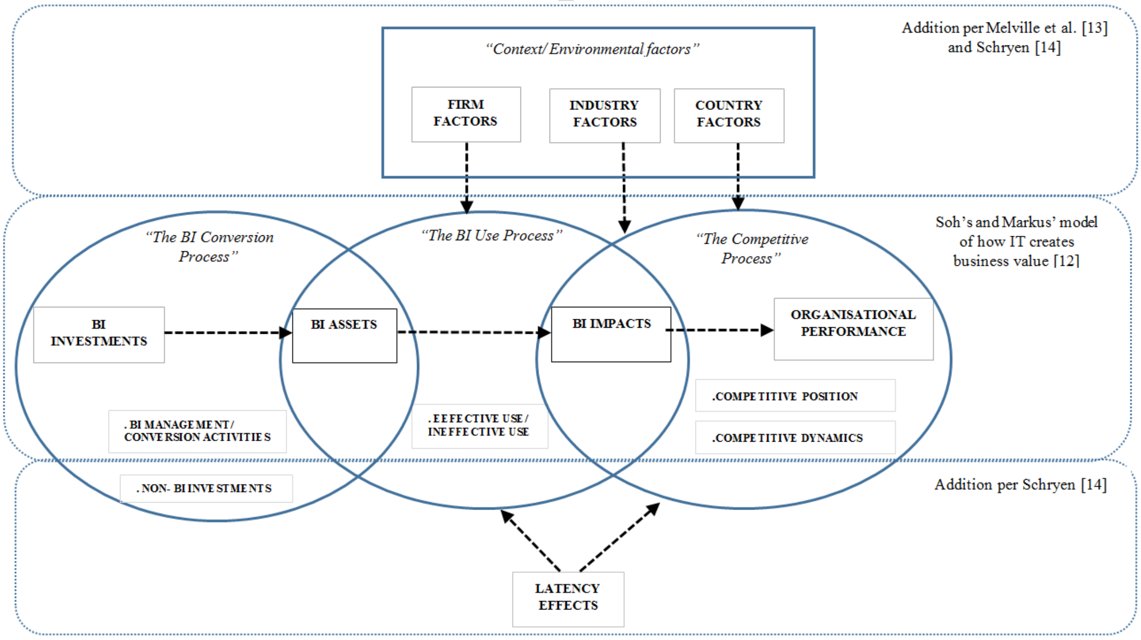

Fig. 2 A framework of how BI creates business value (adapted from [12, 13, 14])

The foundation of Fig. 2 is the seminal model of Soh and Markus [12]. In their paper, Soh and Markus described the theoretical difficulties researchers were experiencing, and the mixed results researchers were obtaining, in research on IT investment and business value. To address these issues, Soh and Markus [12] proposed a model to explain how the effects of IT play out across a chain of interrelated, yet uncertain outcomes. They used a 'process model' to describe the relationship, and argued that it could help researchers to explain uncertain outcomes better than a variance model could

[24]. Whereas variance models account for uncertainty through moderator variables, process models model the underlying probabilistic processes through which outcomes occur [12]. Although published over 20 years ago, the Soh and Markus model remains influential today. For instance, it has been cited as an exemplar for its ability to support cumulative theory building [25 p.5], it continues to be used as a theoretical foundation in leading articles [26 p.63], and it has been recommended as a valuable guide for future research and practice [27 p.832].

As in [12], the basic idea of the framework in Fig. 2 is that the link from BI investments to organizational performance can be modelled as a chain of necessary conditions, such that increases in organizational performance require a necessary degree of BI impacts, which in turn require BI assets, which, finally, require BI investments. Following the logic of process models [12] each link in the chain reflects a probabilistic process. For instance, the link from investments to assets involves the process of BI management/conversion and investment in complementary (non-BI) investments, the link from BI assets to BI impacts depends on the process of using BI systems effectively, and the link from BI impacts to organizational performance depends on the competitive process [12].

The model of Soh and Markus [12] offers explanations of both certain and uncertain outcomes - sometimes occurring, sometimes not. Uncertain outcomes are a major focus of the model [24]. The occurrence of uncertain outcomes indicates that necessary conditions are not sufficient to produce outcomes. The Soh and Markus model [12] provides a comprehensive account of how value is obtained (or not) from IT. However, it can be improved. In particular, recent studies stress that the ultimate outcome of IT investment can take time to evolve [21] and can be affected by external forces [12] such as context, environment [13], and time lags [14]. Fig. 2 incorporates these more recent ideas (especially those of Melville et al. [13] and Schryen [14]), into the framework for this study.

Fig. 2, therefore, reflects a synthesized theoretical framework for BI business value. It accounts for three value generation processes (the conversion process [12, 14], use process [12], and competitive process [12]), as well as context/environmental factors [13, 14], and latency effects [14]. Overall, it suggests that BI business value generation involves the following set of necessary conditions and probabilistic processes: organizations invest in BI, and subject to the varying degrees of effectiveness during the BI management process and non-BI investments [13, 14], obtain BI assets. Quality BI assets, if used effectively [12, 13], then yield desired BI impacts, which help yield organizational performance [12]. Context/environmental factors include firm (or organizational), industry, and country factors [14] that influence the BI use process and the competitive process. Firm factors can also influence the BI use process, whereas both industry factors and country factors influence the competitive process [13, 14]. Latency effects need to be considered to account for organizational learning and adjustment [14].

This review follows the structure of Fig. 2. Specifically, prior studies are reviewed to identify predominant, unexplained, and partially unexplained areas in the BI business value theoretical framework. Moreover, attention is given to the level of analysis at which papers have focused (i.e. individual, workgroup, organization, industry, and society), [28, 29] given the importance of accounting for levels when studying business value of IS [14, 22, 30-32] . The findings are then used to develop a comprehensive research agenda for future work.

2.3. Coding Process

To ensure reliable coding, two coders were used, the author and a research assistant. Both coders read the articles and coded them based on the concepts and relationships in the framework (Fig. 2) to determine if/how each article examined each element in the framework. A key step in this task was to distinguish between cursory and detailed discussions [33, 34]. The term ‘cursory’ is used to describe a paper that refers to a concept in the framework only briefly or at a high level of abstraction. In contrast, the term ‘detailed’ is used to describe a paper that refers to a concept in the framework in detail and often at a lower level of abstraction. For example, Clark et al. [35] wrote: *the ‘level of use’ construct must capture more than just the initial usage and incorporate usage over time*. We coded this as cursory because it did not provide any detail regarding what ‘use over time’ involves (such as type of use, length of time). An example of a paper that examined a construct in detail was Dinter [36], which developed and tested measurement items for the construct “*effective use”* and wrote that *effective use of BI is measured by contribution to increase the business value in the organization, contribution to reduce costs in the organization, and synergies in the BI system.* While the cursory/detailed distinction is subjective, similar distinctions have proven helpful in past studies of this type [33, 34]. Moreover, to deal with the subjective nature of the coding, the two coders made their assessments independently.

Initially, each coder independently coded 20 papers. They then compared and discussed their results to assure coding reliability and consistency. Each article was coded against 13 codes, and the inter-rater reliability between the two coders' codes (Cohen's Kappa) ranged from 0.73->1.00 with an average of 0.88 (see Table 2), indicating high agreement [37, 38]. Differences in opinion were resolved through discussion until both coders agreed on all 13 codes and all cursory/detailed distinctions for each of the initial 20 papers. The remaining 86 papers were then distributed equally, with each coder independently working on 43 papers. In addition to coding each article against the 13 codes in the overall framework, the coders also noted more general characteristics of each article (its research question, methodology, and research model) to ensure that they understood each article fully.

3. What We Know

The analysis was conducted in three phases. First, a broad sense of how many articles study BI business value was obtained. Next, papers were reviewed and synthesized for each concept in the BI business value framework. Finally, relevant aspects of these studies as appropriate for each concept and the relationships between them were explored.

3.1. Results by Journal, and by Year

Fig. 3 and 4 show how BI papers have been published by journal and by year. The data shows that BI research has been present in each journal. The higher numbers in MISQ and DSS are to be expected as they are leading outlets for research on the managerial implications of IT [33] and for research on decision-oriented systems. The spike in 2012 could be partly attributed to the special issue

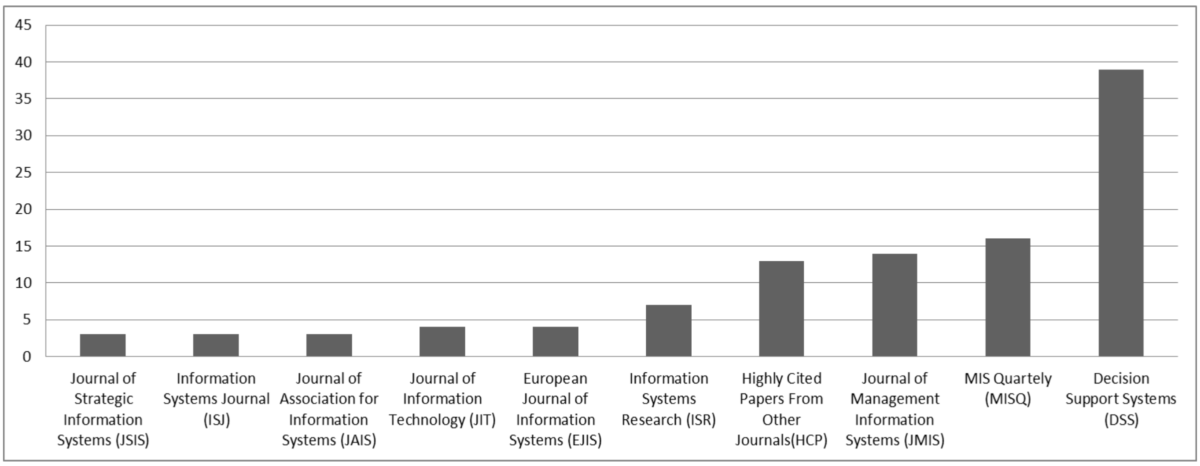

Fig. 3 The sample of 106 reviewed articles by journal

on BI in MISQ in 2012 and practitioner interest around this time [39 p. 47, 40].

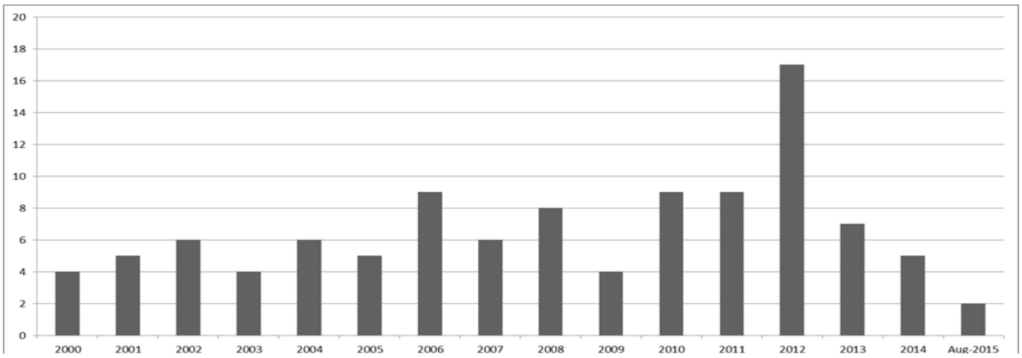

Fig. 4 The sample of 106 reviewed articles by year

3.2. Results of Reviewed BI Studies to the Overview Framework

Table 2 record the degree to which the reviewed BI papers refer to the elements of BI business value and also maps all the papers (both cursory and detailed) to the concepts by percentage, while Fig.5 maps them by areas in the overview framework (Fig. 2).

Table 2
The sample of 106 reviewed papers (cursory and detailed papers) by percentage and concepts in BI business value framework

Concepts	Kappa Score	Total # (%) of papers	# (%) of detailed papers	Papers	# of cursory papers	Papers
BI investments	1.00	20(19%)	10 (9%)	[41-50]	10 (9%)	[51-59]
BI Management/Conversion activities	0.93	31(29%)	13(12%)	[35, 41, 55, 56, 60-67]	18 (17%)	[11, 36, 40, 50, 51, 53-55, 68-77]
Non-BI investments	1.00	3(2%)	2 (2%)	[41, 45]	1 (1%)	[40, 41, 45]
BI assets	1.00	98 (92%)	60 (56%)	[35, 36, 40, 41, 44, 47, 48, 50, 52, 53, 55, 71, 72, 75, 76, 78-122]	38 (36%)	[9, 11, 42, 43, 45, 46, 49, 51, 55-58, 61-66, 68-70, 74, 77, 79, 95, 123-135]
BI Effective/Ineffective use	1.00	5 (5%)	3 (3%)	[11, 36, 136]	2 (2%)	[35, 70]
BI impacts	0.93	78 (67%)	26 (24%)	[35, 41, 43, 47, 50, 55, 56, 60, 62, 63, 69, 72, 80, 81, 83, 91, 94, 95, 97-99, 123, 126-128]	52 (49%)	[11, 36, 42, 44-46, 49, 51-53, 57-59, 64-68, 70, 73, 77-80, 82, 84-86, 88, 89, 94, 101-106, 109-112, 115, 116, 118-120, 124, 130, 131, 133-135, 137]
Competitive dynamics	0.87	3 (3%)	0 (0%)	None	3 (3%)	[62, 70, 73]
Competitive position	0.73	3 (3%)	0 (0%)	None	3 (3%)	[70, 79, 85]
Organizational performance	0.77	26 (24%)	13 (12%)	[43, 45, 51, 53, 55, 56, 59, 60, 62, 77, 79-81]	13 (12%)	[9, 42, 48, 49, 54, 55, 58, 69, 74, 100, 109, 113, 137]
Firms factors	0.76	15 (14%)	7 (6%)	[45, 56, 58, 61, 69, 134]	8 (7%)	[9, 36, 54, 62, 73, 79, 121, 123]
Industry factors	0.8	26 (22%)	7 (8%)	[62, 69, 77, 80, 81, 85, 86]	19 (14%)	[11, 36, 40, 45, 49, 51, 54-56, 60, 61, 73, 98, 100, 105, 109, 113, 123, 136]
Country factors	0.73	1 (1%)	1 (1%)	[79]	0 (0%)	None
Latency effects	1.00	7 (7%)	5 (5%)	[11, 36, 55, 62, 77]	2 (2%)	[94, 137]

As noted earlier, the purpose of this study is to suggest an agenda for future BI research based on answers derived from the literature regarding the research question: *What do we know, how well do* *we know, and what do we need to know about the processes of organizations obtaining business value from BI systems?* This review of BI studies yields the framework in Fig. 5, in which the degree of shading reflects the amount of attention each element has received in the literature. Synthesizing the discussion to this point, this question can be answered by stating that from the reviewed literature, organizations appear to obtain value from BI systems according to the process suggested by Soh and Markus [12] as a chain of necessary conditions from BI investments to BI assets to BI impacts to organizational performance. However, as Fig. 5 also shows, the various probabilistic factors have been rarely studied, limiting the ability of researchers to understand how inputs link to outputs.

The following sections describe the results of the literature review in more depth and suggest opportunities for research. The opportunities identified are inevitably influenced by the framework and the approach used for sampling articles. Nevertheless, based on the large set of articles reviewed, each of the opportunities noted below is significant. Working backward, each concept and relationship is discussed, beginning with the ultimate outcome of interest: Organizational Performance.

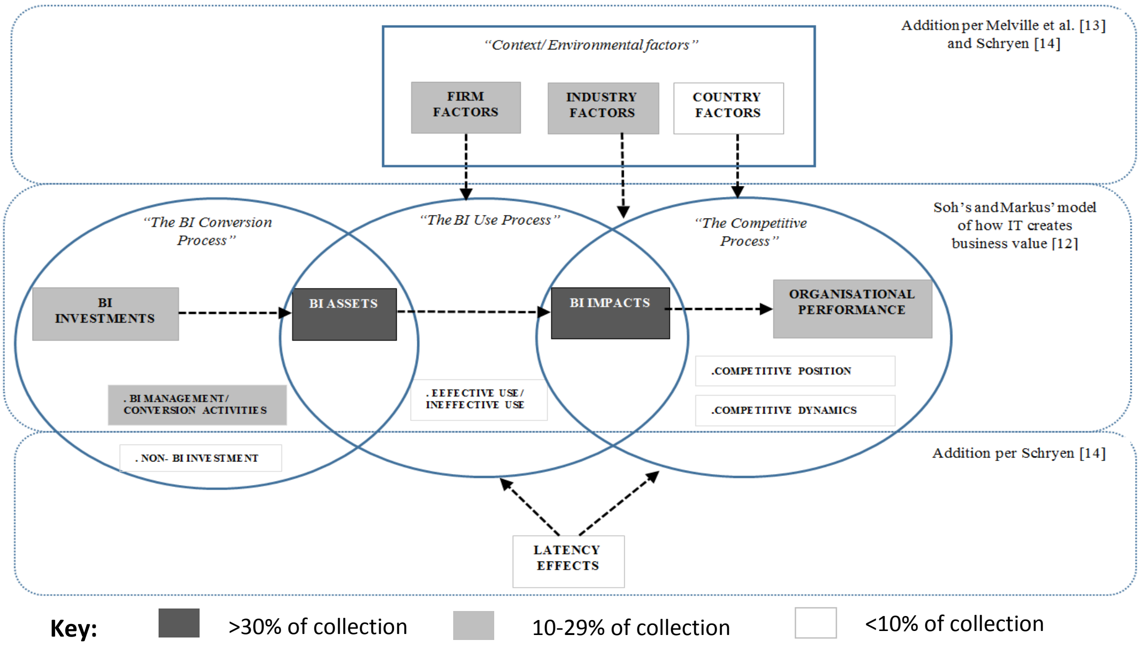

Fig. 5 How BI business value has been studied

3.2.1. Organizational Performance Improvement

According to Soh and Markus [12], conceptualizations of organizational performance depend on how organizations are viewed. They describe three approaches [12]. First, organizations may be viewed as rational; with measures of performance that reflect successful goal accomplishment. Second, organizations may be viewed as coalitions of power constituencies; with performance measured through the satisfaction of constituents such as employees and customers. Finally, they may be viewed as entities ‘involved in bargaining relationships with their surroundings, importing various scarce resources to be returned as valued output’ [12 p.36]; measures of performance appropriate to this perspective include the organization’s ability to obtain scarce resources and productively turn them into valued outputs [12]. Since all three main perspectives on organizations are simultaneously valid in most organizations, explorations of organizational performance need to consider all measures of performance that reflect the different perspectives of organizations.

The review shows that of 106 papers, 26 papers discussed organizational performance improvement with regards to BI investment. *Organizational performance*, in turn, was discussed through the first approach of goal-seeking and goal accomplishment perspectives including productivity [43, 52, 53, 79] and revenue [59, 60, 81]. It also was studied through the second approach of constituents’ satisfaction, e.g., customer satisfaction [42, 46, 68, 77] and employee satisfaction [62]. Finally, it also was examined through the third approach of productivity including obtaining and allocating scarce storage resources to reduce cost [49, 69] and the garnering of skills necessary to perform critical functions within firms to achieve desired outcomes [65].

3.2.2. BI Impacts

Reading backwards from *Organizational Performance*, *BI Impacts* are the first necessary condition for improved organizational performance [62]. *BI Impacts* refer to a state when organizations have achieved one or more of following outcomes: improved operational efficiency of processes; new/improved products or services; and/or strengthened organizational intelligence and dynamic organizational structure [12, 13].

The review shows that *BI Impacts* have been a main focus of BI studies for the last 15 years. Researchers have shown, in particular, that BI can be used to improve a firm’s operational efficiencies by minimising the mis-targeting customers [42], transforming business processes [42, 45, 59, 62, 82, 138], enriching organizational intelligence [59, 79, 81, 85, 89], and developing new or improving products or services [11, 68, 82, 86, 88]. However, the BI literature has been silent on how these *BI Impacts* complement other internal and external factors to create business value.

3.2.3. Competitive Process: From BI Impacts to Organizational Performance

Having discussed *Organizational Performance* and *BI Impacts*, the link between them is now examined. IT impacts are important and necessary but not sufficient to result in improved organizational performance if business conditions are not favourable. Based on the IT value models [12-14], summarised in Table 3, the necessary conditions and probabilistic factors that these models suggest are critical for BI impacts to improve organizational performance include the competitive position of an organization, competitive dynamics, industry and country factors, and latency effects. These concepts and other aspects of Table 3 are discussed below.

Table 3
From BI impact to organizational performance (Based on [12-14])

Process theory and focal unit [12]	**Outcome [12]**	**Necessary conditions [12]**	**Probabilistic processes [12] and external directional forces [13, 14]**
-Enhanced organizational effectiveness -Focal unit is the organization	-Improved *organizational performance*	-*BI impacts*: organizational impacts due to BI investment	**Probabilistic processes per Soh and Markus [12]:** *1. Competitive position* 2. *Competitive dynamics*: competitor and customer reactions **External directional forces per Schryen [14], and Melville et al. [13]:** *1. Industry factors:* regulation, competitiveness, technological change, BI standards and time-sensitiveness, technology standards. *2. Country factors:* laws and country's technological infrastructure, IT culture. *3. Latency effects:* - Latency effects due to required time for adaptation, implementation, acceptance - Latency effects due to time needed to adjust to the new technology, or for the technology to mature - Latency effect due to learning or adjustments

3.2.3.1. Competitive Position

A strong initial competitive position in the competitive landscape in which a firm operates is a favourable business condition contributing to the positive linkage between BI impacts and organizational performance improvement. With a strong competitive advantage, the focal firm should be able to convert favorable BI impacts into organizational performance improvement.

In the collection of reviewed BI papers, no studies were found that empirically examined the relationship between IT impacts and improved organizational performance through favourable competitive position. However, there are a few BI studies (3%) that briefly discuss the "competitive position” of organizations in a cursory fashion. For example, Lau et al [79] mention the competitive position of organizations through their discussion of BI business relation mining techniques to estimate the strength of organization’s competitiveness. In addition, Rouibah and Ouldili [85], and Schultze [70] give a cursory glance towards competitive position through an explanation of using BI to query the status of competitors or monitor a competitor’s competitive position.

3.2.3.2. Competitive Dynamics

Competitive dynamics (on the right hand side of Fig. 5) have been recognised as key factors in organizational performance [73]. Soh and Markus [12] argue that favourable competitive dynamics (i.e. non-response or slow response from competitors) is one of the probabilistic supporting conditions for *BI Impacts* to result in *Organizational Performance*. If firms benefit from rich organizational intelligence and new and improved products and services from BI (i.e. *BI Impacts*), the degree of competitive pressure from competitors on firms will be reduced [73]. Studying competitive dynamics in the BI context will help to better understand how *BI Impacts* can be converted into organizational performance improvement. However, of the 106 reviewed papers, only three discussed competitive dynamics. In addition, these studies were coded as cursory as they simply referred to a very general idea or limited idea of competitive dynamics; e.g., providing very limited discussion of competitor’s reactions to BI application [70] or firm’s reactions to industry pressure to adopt BI [72, 73].

3.2.3.3. Industry Factors

Industry characteristics ground the way in which BI is applied within a focal firm to generate business value and include competitiveness, regulation, and velocity of change [13]. The results of examining industry factors in BI studies show that a fully configured BI system provides differential value based on the types of industry in which a firm operates [62, 69, 85, 86]. For example, Elbashir et al. [62] explain that non-service industries show stronger relationships between *BI Impacts* and *Organizational Performance* than service industries, arguing that the non-service sectors appear to be able to convert BI impacts more effectively into organizational performance enhancements. On the other hand, the velocity of change in the service sector is faster than non-service sector, due to faster customers and competitor reactions, making real-time data vital for decision-making [77]. For example, the clockspeed in banking is described as very fast, such that "if the magnitude of a market shock exceeds a certain threshold, contagious bank failures will happen with accelerating speed" [80 p. 1289]. In such an example, the adoption of strong BI risk mitigation to predict contagious bank failures and determine capital injection priorities post crises assists bank survival.

Regarding differences in industry regulation, Abbasi et al. [81] report that regulation is heavy, for example, in the auditing sector since regulations restrict auditors from accessing internal data until an audit or investigation takes place. They suggest that firms could use BI tools together with publicly available information for better decision-making and for prioritisation of investigative resources.

Overall, while industry factors have received moderate attention (22%) in BI research, there is still a lack of studies investigating industry factors in terms of technological change and BI standards.

3.2.3.4. Country Factors

Country factors denote the country and meta-country characteristics (e.g. law, infrastructure, culture) that influence BI applications for organizational performance improvement [13]. For example, Melville et al. [13 p. 297] note that: "[…] firms in developing countries face constraints in applying information technology in the areas of education, expertise, infrastructure, and culture [139]"

The reviewed papers show that BI business value research has examined firms in the U.S. [11, 61, 77], Brazil [51], China [79, 110], Slovenia [123], and across-countries [40, 45, 74, 105]. However, discussions on the effect of country factors on BI business value are mostly cursory. Only one study by Lau et al [79] highlighted the country characteristics in terms of law and regulation that impacted *Organizational Performance*. Lau et al. [79] explain that the cross-border mergers and acquisitions of some Chinese companies, such as in the U.S., have encountered serious challenges because of the Chinese companies' lack of knowledge about the socio-cultural and political-economic characteristics of the targeted merger and acquisitions environment.

3.2.3.5. Latency Effects and Competitive Process

Latency effects have been identified as important in assessing BI business value because a period of time may pass before an organizational investment in BI yields positive results [14, 140]. It is therefore important to consider latency effects when investigating BI business value; Sharma et al., [141 p. 191] note that: "performance gains from business analytics cannot be planned or predicted at the time an organization makes its investments in the business analytics infrastructure." Improved organizational performance can be delayed because organizations need some lag or adjustment time to match organizational factors and BI investments [21]. For example, time since adoption of a system affects business value because a longer period from adoption may enable organizations to develop expertise to use the system more effectively to generate business value [14, 142]. Therefore, we would expect to see more benefits over longer time periods [14, 140].

The review results show that the number of papers discussing latency effects in this review is limited (only 5% of reviewed papers). For example: latency effects due to time needed to adjust application silos, low process integration into integrated BI technology [69]. Dinter [36] found that time since adoption significantly impacts the effective use of BI because of time needed to develop mature BI data quality management. However, Elbashir et al. [62] claim that time since adoption does not affect the ability of an organization to convert BI impacts into organizational performance. These paradoxical results would seem to present a good opportunity for future research.

Summarizing these five subsections, the review of BI research suggests that *BI Impacts* will confer benefits to *Organizational Performance* if they are supported by favourable competitive position, competitive dynamics and country factors.

3.2.4. BI Assets

Again, reading backward from *BI Impacts*, the presence of *BI Assets* is a necessary condition for firms to achieve *BI Impacts* such as new products/services, redesigned business process, better decision-making and business process performance improvement. According to Soh and Markus [12], *BI Impacts* are an uncertain outcome of a conversion process in which *BI Assets* play a role as a vital condition to result in the outcome. *BI Assets* consist of BI technology, human resources and application portfolios [12, 143].

The topic of *BI Assets* has received much more attention than the other areas. Of the reviewed papers, 98 of 106 (91%) discussed *BI Assets* in either a detailed or cursory fashion. In terms of BI technology, the results illustrate high quality BI technology is recognized as BI tools designed in a way that fits an organization's task and data strategy, combined with hardware infrastructure that can quickly churn large amounts of data. In addition, high quality hardware is a necessary factor to make BI a viable tool for decision-making under uncertainty [83] especially as today BI organizations are moving from high up-front hardware investment to lower scalable monthly cloud service to provide services (e.g. Software as a Service, Platform as a Service [89], Infrastructure as a Service [99]) which offers 'cost-saving, better performance and faster access to new applications'[89 p. 399]. However, despite the importance of BI hardware quality, BI hardware artefacts (e.g. data blades and BI appliances) have not attracted BI researchers' interest. In the collection of studies on *BI Assets*, very few discussed hardware infrastructure and those that did so were cursory. For example, Lee et al. [98] claim that hardware improvement is one of the factors that can help managers successfully develop a churn management program and retention strategies. Therefore, future research may need to investigate the technology of virtual hardware and hosted technologies that support cloud computing services as alternatives to traditional and physical hardware[1].

In comparison with hardware studies, BI tools have become a dominant research area in the literature and they are investigated in a detailed fashion. For example, there has been detailed discussion of BI methodologies and techniques [75, 97, 100, 131], predictive models [42, 45, 68, 80], and BI interfaces [46, 84, 97].

Regarding the human resources perspective on *BI Assets*, skilled employees and skilled analytical staff are highlighted as important BI human resources that benefit organizations in creating business value. Studies have suggested or shown that humans are the primary resources for BI success [35, 49, 83, 96] such that organizations are encouraged to bring the analytical talents and other skills of employees together to pursue better services and customer satisfaction [55, 63, 68, 77, 105].

In summary, the literature suggests that sophisticated BI and high quality BI human resources are favourable *BI Assets* which are recognised as a necessary condition for positive *BI Impacts*.

[1] I thank an anonymous reviewer for this insight

3.2.5. BI Use Process: From BI Assets to BI Impacts

According to [12], high quality *BI Assets* are a necessary, but not sufficient condition, to result in *BI Impacts*, because any process losses of system development cycle time, business operations productivity, and BI planning can reduce effectiveness and result in negative impacts. Therefore, impacts from BI require effective BI use. In addition, when investigating the linkage between *BI Assets* and *BI Impacts*, firm factors and latency effects need to be taken into consideration because they affect the success of the conversion of quality *BI Assets* into *BI Impacts*. Based on the IT value models [12-14], Table 4 summarises the business related factors [12-14] and necessary conditions [12] for *BI Assets* to result in improved *BI Impacts*, showing that the pathway from *BI Assets* to *BI Impacts* is affected by the effectiveness of BI use, firm factors, and latency effects.

Table 4
From BI assets to BI impacts (Based on [12-14])

Process theory and focal unit [12]	**Outcome [12]**	**Necessary conditions [12]**	**Probabilistic processes [12] and external directional forces [12-14]**
-BI impacts -Focal unit is the organization or subset (e.g. business unit, functional area, business process)	-BI impacts	-BI assets	**Probabilistic processes per Soh and Markus [12]:** • *Effective use/ineffective use:* Individual discretion in complying with firm directives **External directional forces Schryen [14], and Melville et al. [13]:** • *Firm factors:* operational capability, organizational practices, firm boundary strategy, firm size, firm culture, geographical dispersion of firm units, analytic and evidence-based decision making culture **External directional forces Schryen [14]:** • *Latency effects:* - Latency effects due to required time for adaptation, implementation, acceptance - Latency effects due to time needed to adjust to the new technology, or for the technology to mature - Latency effect due to learning or adjustments

3.2.5.1 Effective Use/Ineffective Use

The impact of *BI Investment* on *Organizational Performance* is mediated by the BI use process in which BI use can have unexpected consequences [14]. To obtain maximum benefit from BI, systems need to be used effectively [144]. Ineffective use of BI likely results in workflow problems that will ultimately impact negatively on business task performance [11].

There are very few empirical studies on the ‘effective’ or ‘ineffective’ use of BI. Of the 106 reviewed papers, 5 were coded as discussing BI effective use of which only three discussed effective use in a detailed fashion [e.g. 11, 36, 136] and two in a cursory manner [35, 70]. Though existing research on effective/ineffective use of BI may pre-date of the study period, the results of an intensive literature review on effective use conducted by Burton-Jones and Grange [144] support the present findings that that there has been a scarcity of studies on effective use and ineffective use in BI context.

While Dinter [36] and Li et al. [136] study BI system use from an effective use perspective, Deng and Chi [11] study ineffective use. Dinter [36] found effective use of BI is related to effective use of information logistics which is in turn driven by BI system quality and adequate information supply. Li et al. [136] report that effective use of BI in terms of routine use and innovative use depends on intrinsic and extrinsic motivations. Regarding 'ineffective use,' Deng and Chi [11] identify seven problems that may cause ineffective use, i.e., problems of reporting, data, workflow, role authorization, user's lack of knowledge, system error, and user- system interaction [11].

Technology per se cannot increase or decrease workers' productivity unless it is used [145, 146] and used *effectively* [144, 147]. Therefore, it would seem from this review that it is critical to have more research on BI effective use given that there is a dearth of research in this area.

3.2.5.2 Firm Factors

The results of comparative studies on firm factors in BI studies show that a fully configured BI system provides differential value to different type of organizations [62]. Organizational size, scope and absorptive capacity all contribute to successful adoption of BI [61].

For example, firm size will affect the ability of the organization to convert *BI Assets* into *BI Impacts* [12] because large organizations are more likely to exploit BI's potential [61] than small organizations. However, Elbashir et al. [62] found that firm size does not affect the ability of the organization to convert BI impacts into organizational performance. Trkman et al. [45] meanwhile explained that implementing BI per se does not necessarily bring benefits to a firm since BI are also about people's views of the value of information, exploratory and predictive models and fact-based management. Several papers have shown or described how a deeply analytical, evidence-based decision-making culture positively affects the use of information in business processes to generate BI impacts [56, 69, 72, 123].

3.2.5.3 Latency Effects and the BI Use Process

Latency effects have been identified as a factor that influences the BI use process [14, 77]. Positive BI impacts can be delayed because of the time required for adaptation, implementation, acceptance [148], data loading [11, 77], or even for analysis tasks and decision made [77]. Latency effects can reduce the improvement of organizational intelligence and operational improvement of the operational efficiency of processes. For example, in customer-facing services such as call centres, check-in processes, and help centres, high-latency data due to delayed data loading might reduce the operational efficiency of the decision-making processes. Also, in the banking, airline and medical sectors, low-latency data has much more value than high-latency data in supporting real-time decision-making and as a result, improves organizational services. Hackathorn [149] and Watson et al. [77] list three kinds of latency that affect BI use process (see Table 5). Overall, by reducing latency, firms can use BI to affect current decision making and business processes such as customer-facing and supply chain applications, ultimately increasing revenues and decreasing costs [77].

Table 5
Types of latency effects on the BI use process.

Latency	Definitions	Latency and BI use process
Data latency	Is the length of time between when an event occurs and when the associated data is stored in the data warehouse	Latency occurs when time is needed for the technology to mature (i.e. length of time that BI is implemented and deployed) to support and to manage real-time data feeds from source systems.
Analysis latency	Is the time between when the data is stored and when it is analysed and made available to applications and users.	Latency occurs when time is needed for data analysis and made available to operational systems and personnel.
Decision latency	Is the time from when the information is available until some action is taken on it	Latency occurs when time is needed for the actions to be taken on the available information.

The results of the review show that researchers paid little attention to latency effects. Of 106 reviewed papers, the coders classified two papers discussing latency effects in cursory manner [11, 62] and five papers discussing in detailed fashion [i.e. 36, 55, 77, 94, 137]. Of these seven papers, we found no paper discussing analysis latency, only one paper discussed decision latency [i.e. 137], and six papers discussed data latency [i.e. 11, 36, 55, 62, 77, 94].

In summary, *BI Impacts* and *BI Assets* are the most intensively discussed factors in the literature whereas latency effects and effectiveness of use in BI contexts are not well-studied. This suggests, on the one hand, that more studies on latency effects and ineffective use are needed to help organizations better understand why and how they can be minimized. On the other hand, more work on effective use is required to understand how to maximize the business value of BI to organizations.

3.2.6. BI Investments

BI Investment consists of investments on BI related hardware, software and technical infrastructure, human resources and management capabilities [14]. As an indicator of its importance, BI technology investment was ranked first globally in 2010 and it remained the top technology investment in 2011 [40]. According to Gartner's [150] research, BI is predicted to remain a top focus for CIOs though 2017, with the scale of investment in BI growing dramatically [53, 62].

The review of the literature shows, however, that not much attention has been paid to *BI Investment*, with 10 of the 106 papers discussing investments in a detailed fashion and another 10 discussing investments in a cursory manner. The research has generally argued that *BI Investments* induce better business performance [e.g., 45, 51, 52, 54]. Some studies are more specialised, and analysed the impacts of *BI Investments* on specific parts of organizations such as relationship-based marketing [42, 43], supply chain management [44, 45], risk management [41], and knowledge discovery and management [46, 47, 50]. However, studies on investment in BI hardware, and management capabilities are scarce.

One reason for the lack of studies on *BI Investments* on software services and hardware could be, as Goasduff and Pettey [151] highlight in Gartner's research, that 40% of spending on BI will go to system integrators and implementation instead of services/software solutions because it is difficult for companies to integrate the external and unstructured data with their structured data. However, this does not explain why investments in management capability are absent in the BI literature.

There have been several studies on investments on BI human resources. For example, in Luftman et al.'s [40] studies, investments on staff retention rates, budget for staff and training for BI staff [49] are reported as increasing trends of investment in organizations [40]. Watson et al. [77] also reported in a case study of Continental Airline that investment in BI hardware, software, and human resources helped the organization generate more than $500 million in revenue. There has been a deficiency of studies discussing the synergies of these *BI Investments* in BI literature.

3.2.7. BI Conversion Process: From BI Investments to BI Assets

Because *BI Investments* are a necessary but not sufficient condition for *BI Assets* [12], managers should identify and consider investments in complementary variables [60] such as non-BI investment [14] and BI management/conversion activities [12] when making *BI Investment* decisions. Table 6 illustrates the relationship between *BI Investments* and *BI Assets* based on the models used in this review [12-14]. As Table 6 shows, the pathway from *BI Investments* to *BI Assets* is affected by the BI management and conversion activities, and non-BI investment factors discussed below.

Table 6
From BI investments to BI assets (Based on [12-14])

Process theory and focal units [12]	**Outcome [12]**	**Necessary conditions [12]**	**Probabilistic processes and external directional forces [12, 14]**
-BI assets -Focal unit is the BI acquisition or deployment project/process	BI assets: -Useful, well-designed applications -Flexible BI infrastructure with good “reach” and “range” -High levels of user IT knowledge and skills	*BI investments* on: - BI hardware, software and technical infrastructure - Human BI resources - BI management capabilities	**Probabilistic processes per Soh and Markus [12]:** • *BI management/ conversion activities* **External directional forces per Schryen [14]:** • *Non-BI investment*

3.2.7.1. BI Management/Conversion Activities

BI management consists of four areas that are strongly associated with BI conversion activities: formulating BI strategy, selecting appropriate organizational structures for executive BI strategies, selecting the right BI projects, and managing BI projects effectively [12].

The results of this review indicate that BI researchers have paid attention to all four areas of BI management associated with BI conversion activities. For instance, determinants of BI strategy formulation [61], implementation of BI strategies associated with the adoption of certain governance practices [69], alignment between BI and business, planning and project management [40], and organizational readiness [35]. Research on the selection of organizational structures in executive BI strategy ranges from discussion of management commitment through to creation of governance structure [51], analysis of the effects of management support on BI deployment [62], and the success of BI implementation [63]. The selection and adoption of BI projects depends on organizations’ goals [73] and its data environment [61]. There are many techniques for managing BI projects effectively such as identifying critical success factors of BI implementation projects [36, 123], and the mediating role of absorptive capacity in the link between BI integration and business performance [54].

However, Soh and Markus [12] stress that BI management strategies and policies are complex reactions to the variety of situations that organizations might find themselves in. While this review identified many papers that examined the general topic of management/conversion activities, not all of these complexities have been addressed, with the review suggesting that more attention needs to be paid to the four areas of BI management that are strongly associated with BI conversion activities.

3.2.7.2. Non-BI Investments

Finally, while *BI Investments* are a necessary condition for *BI Assets* to occur [12], when BI investments and non-BI investments are complemented, together they affect the process of business value generation [14]. For instance, Ko and Osei [60] claim that improved organizational performance cannot be expected from BI investments alone but only together with non-BI investments.

As reflected in Fig.5, inadequate attention has been paid to non-BI investments, with only two of the reviewed papers discussing non-BI investments in a detailed fashion: i.e. risk investment [41] and investment in practice of sales and operation planning [45]. This review would suggest, therefore, that this is an important area for further work.

3.3 Results of Reviewed BI Studies by Level of Analysis

As suggested by literature [e.g. 28, 29], this review also considers the level of analysis at which BI value is realized. Fig.6 shows that while organizational level of analysis is the main focus of reviewed papers (84 studies), and individual level of analysis received moderate attention (15 studies), little attention was paid on other levels. In particular, only two studies focus on industry level, one study on the society level, one on the team level, and three studies conducted multi-level analysis.

At the individual level, the literature review shows that BI systems help improve individuals' decision-making performance [49, 97, 130] by enabling sensemaking in data exploration tasks [46, 50, 97, 118], facilitating analysis of large volumes of data [136], and enriching knowledge [70, 92, 119]. Individual-level inhibitors also need to be addressed (e.g., role authorization) [11].

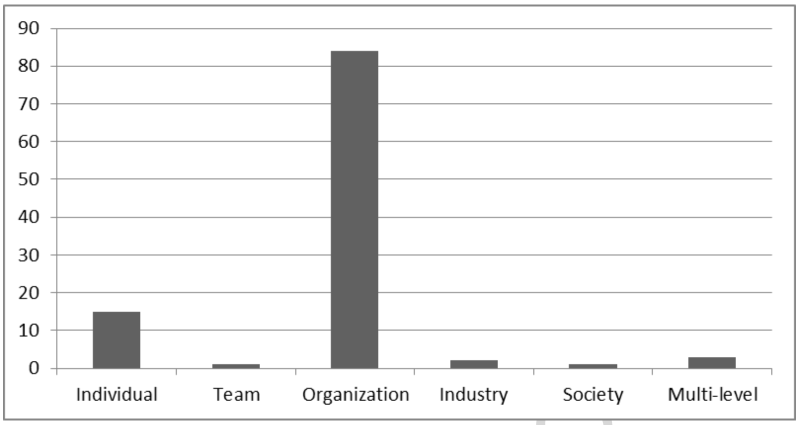

Fig. 6 The sample of 106 reviewed articles by level of analysis

At the team/group level, there has been very little work. Nonetheless, Lin et al. [110] found BI adoption can enhance team productivity by facilitating team coordination and collaboration streamlines the collection and analysis of project documents throughout project life cycle.

At the organizational level, BI research finds positive correlations between BI and productivity [e.g. 41, 65, 72, 79, 81, 123]. For examples, Dinter [36] found the impacts of BI on productivity of organizations affected by the comprehensiveness, flexibility, support, communication, BI strategy orientation, business/BI partnership, and project collaboration of BI adoption strategy. Moreover, Wixom and Watson [63] suggest that at a macro-level, BI business value is greatly supported by BI management and conversion success including the success of organizational implementation, project implementation and technical implementation. However, they note that at micro-level, it is most likely that the BI technical issues vary with the nature of the infrastructure BI project of individual firms [63]. Therefore, the BI impacts may be different among different organizations depending on the variety of complementary, probabilistic factors, and situations that the organizations might find themselves in [60].

At the industry level, researchers report positive impacts of BI on industry productivity. For instance, BI adoption in public health can accelerate the process of understanding public health issues and responding to crises [102]. Likewise, BI adoption in banking can increase detection of and response to fraud [132]. Meanwhile, at the societal level, De Cnudde and Martens [107] report BI systems support a city in Belgium increase active user base of a loyalty card to promote their citizens participation in cultural services offered by the city.

There have been very few multilevel studies. In one of the few studies, Ang and Teo [64] describe how BI systems support decision makers in Singapore making better decisions on providing affordable, high-quality public housing which ultimately results in an efficient and effective civil service for country. Similarly, in a Chinese context, Peng et al. [94] report BI systems enable decision makers to evaluate risks and select an appropriate solution during disaster management. Finally, researchers have implemented well-designed strategic BI systems to support managers in practice to handle weak signs more effectively and thereby ensure the success of the organization's strategy [85].

Overall, the review results align with findings from the broader IS literature [i.e. 23, 152]: that the impact of IS on productivity generally appears more positive in research that has better data sources, refined productivity measures, and a better account of the management aspects of IS [152].

4. What We Need to Know

As noted earlier, the focus of this study has been to learn which parts of the BI business value framework have attracted researchers' attention and what opportunities these offer for future research. The analysis reveals five broad themes that could motivate further work. Research questions corresponding to each of the five themes have been identified (See Table 7). While these opportunities are not the only ones, the results of the literature review suggest that they are significant.

Having analysed a substantial body of literature on BI at different level of analysis, the review suggests a need of research at macro level i.e. at team, industry, and society level of analysis because (1) IT become a larger share of capital investment at national and society level [23]; (2) BI can be adopted to support inter-organizational efficiency, coordination with suppliers [62] and with team [7] , and provide positive returns [14, 23]. This paper also calls for more papers rigorously conducted at multiple levels of analysis given that there have been very few researchers conducted multi-level empirical studies, and many of them [e.g 85, 94] did not account for the effects of interdependencies between individuals [153].

Table 7
Gaps in and proposed paths for BI business value research

Theme	BI business value concepts	Gaps in research	Research questions	The value of addressing the gaps	Proposed research approaches
Theme 1: Context/ Environmental factors	**Firm factors**	The relationships between BI business value and organizational change, organizational practices, organizational resources, and operational capabilities need to be uncovered.	-How do changes in organization structure influence the ability of BI impacts to generate business value? -How can BI resource allocation and resource orchestration improve BI effective use?	To understand the dependence of BI business value on organizational structure [33], changes [13], resources allocation [69], and orchestration [154].	Addressing from a resource based view [155], resources orchestration view [154] and/or an organizational structure perspective [24, 156].
	Industry factors	Impact of technology change and BI technology standards environment (that firms operate in) on BI business value creation is little understood	-How do BI technology standards in industries shape an organization's competitive position? -How do the changes of BI technology standards in industries influence the competitive dynamics of organizations?	To help draw a clearer picture of the role of industry characteristics in shaping the application of BI for improved organizational performance	Drawing on an inter-organizational evolution perspective [157]
	Country factors	Country factors that affect the processes through which organizations obtain business value [13, 14] from BI systems have hardly been studied	-How do existing country characteristics influence the ability of BI based organizations to yield business value?	To help organization managers make better strategic decisions on formulating BI investment and adoption in different countries.	A polycontextual lens that considers each country's level of development, education, culture, basic infrastructure [13, 158], and law and technology regulations [14].
Theme 2: BI conversion process	**BI Investment**	The complementarity of different types of BI investments in creating business value has not been considered sufficiently.	- How do BI investments affect each other and jointly create business value?	Allow for the systematic and generally applicable identification of the linkages and complementarities of different BI investments serving BI business value generation	Addressing from Choo and Shaw's [159] ideas of IT synergy in IT portfolio selection
	BI management/ conversion activities	Investigation is needed into BI management practices and conversion activities that improve operational efficiencies and competitive advantage [160].	- How can we make decisions on the focus of BI development and maintenance to improve operational efficiencies and competitive advantage? -How do reconfigurations of organizational routines impact BI operational efficiencies?	To better understand how BI management strategies and policies are complex and context-dependent. Additional studies in this area would help to capture and highlight the richness of the issues.	Applying a grounded theory research approach to explore answers to these questions.
	Non-BI investments	Only little is known about non-BI investments even though these have substantial impacts on the process of BI investments creating business value [14, 41, 60].	-How do non-IS investments influence the effective use of BI?	To help organizations plan to prevent and to control its key risks.	Identifying various functional processes and dynamic business capabilities [21] and the various condition needed for BI usage.
	BI assets	Few studies discussed either the role of synergies between BI systems and other systems, or the role of BI hardware infrastructure,	-How do BI cloud computing services and virtual hardware generate operational efficiencies and competitive advantage? -How do BI systems synergistically work	To understand the role of synergies between BI systems and other systems, or the role of BI hardware infrastructure in facilitating the use of BI to generate	Taking a system-lens such as systems theory [161] or IT enterprise architecture [162]

		such as the emergence of virtual hardware and hosted technologies	with other systems within the organization to create business value?	business value	
Theme 3: BI use process	**Effective/ ineffective use**	Remarkably little attention has been paid to concepts of effective use in the BI literature	-What drives the effective use of BI systems?	To help firms to improve their level of effective BI use in the pursuit of better organizational performance and improved business value.	Taking different theoretical perspectives such as the theory of effective use [144], adaptive structuration theory [163, 164], and creative use [165], or conducting inductive research to develop a new theory to draw a richer picture of BI effective use phenomena.
	BI impacts	Lack of studies on the role of complementarity between BI impacts and internal and external factors in generating business value.	-How do BI impacts complement internal and external factors to create business value?	To help organizations better understand the link between BI impacts and organizational performance which is simultaneously dependent upon external and internal factors [13]	Applying the grounded theory techniques to approach and explore this complex phenomenon.
Theme 4: BI competitive process	**Competitive position**	No empirical studies were found that examined competitive position or/and dynamics in BI contexts in a detailed fashion.	-How does the effective use of BI systems contribute to securing an organization's competitive position? -How do BI impacts complement firm's competitive position to create business value?	To better understand how companies can leverage BI systems to help improve their competitive advantages [45, 61, 166]	Investigating competitive position and competitive dynamics from an organizational ecology view [167]
	Competitive dynamics	No empirical studies were found examined competitive dynamics in BI contexts in a detailed fashion	-How do firm's competitive dynamics influence business value arising from BI effectiveness?	To better understand the relationships between competitive advantages achievement and BI effectiveness [45, 61, 166]	Investigating competitive position and competitive dynamics from an organizational ecology view [167]
	Organizational Performance	Performance, measured as stakeholders and employee satisfaction, was largely overlooked in the BI literature.	-How can employee satisfaction shape BI business value?	To help organizations overcome changes during the BI systems implementation stage.	Drawing on behavioral factors such as employee' satisfaction [168] and behaviours [169]
Theme 5: Latency effects	**Latency effects**	Very little attention in the literature (5% of reviewed papers) has been paid to latency effects	-How do latency effects influence the effective use of BI and firm performance?	To help organizations better understand and mitigate the effects of latency on BI business value.	Drawing on latency effects suggested by Watson et al. [77], and Hackathorn [149], or conduct inductive research to investigate the phenomena.

5. Limitations

Although great care was taken to review the literature thoroughly, three limitations should be noted. First, the study only examined the attention that researchers paid to particular constructs and relationships in their research. The review did not include a quantitative evaluation of the strength of relationships among concepts in the framework. A meta-analysis could be conducted, as a next step, to extend this study. Second, the findings of the review and the opportunities identified are inevitably limited by the framework adopted and the approach taken to sampling articles. An alternative style of review (e.g., using a grounded theory approach, or using a different framework) could identify additional or different insights. Third, the literature was coded by two coders, but only the first 20 papers were coded by both coders. Nonetheless, the kappa values on the first 20 articles was high, suggesting that the approach used for coding the articles was sufficiently reliable.

6. Conclusion

In this paper, a literature review of empirical studies in business intelligence was conducted to examine research into the processes of organizations obtaining value from BI systems by learning from the IS field's empirical BI studies. Through the discussion, gaps in current BI research have been identified as opportunities for future work.

Generally, the BI literature was found to be lacking an overarching framework to systematically guide future research and to integrate findings. The framework proposed in Fig. 2 can potentially provide an overarching theoretical framework for understanding how organizations obtain value from BI systems. In terms of the results of this review, it appears from the literature that a series of necessary conditions [12] from BI investments to BI assets to BI impacts to improved organizational performance, has received much attention from researchers in the field. However, this review shows that researchers have not sufficiently studied the probabilistic processes [12-14] that link the necessary conditions together. Each of these links deserves more attention. In addition, the review results also show a lack of studies conducted at team, industry, and societal levels, as well as a lack of multi-level studies. With more studies of the probabilistic processes across different levels of analysis, we will be able to provide a fuller picture of how business value is generated from BI.

References

[1] R. Agarwal, V. Dhar, Editorial—big data, data science, and analytics: The opportunity and challenge for IS research, Information Systems Research, 25 (2014) 443-448.
[2] A. Shollo, K. Kautz, Towards an understanding of business intelligence, In the Proceedings of the 21st Australian Conference in Information Systems (ACIS), Brisbane, 2010.
[3] M. Gibson, D. Arnott, I. Jagielska, Evaluating the intangible benefits of business intelligence: Review & research agenda, Proceedings of the 2004 IFIP International Conference on Decision Support Systems (DSS2004): Decision Support in an Uncertain and Complex World, 2004, pp. 295-305.
[4] R. Sabherwal, I. Becerra-Fernandez, Business intelligence: Practices, Technologies, and Management, John Wiley & Sons, NJ, 2011.
[5] Z. Jourdan, R.K. Rainer, T.E. Marshall, Business Intelligence: An Analysis of the Literature 1, Information Systems Management, 25 (2008) 121-131.
[6] P.B. Seddon, D. Constantinidis, H. Dod, How Does Business Analytics Contribute to Business Value?, Proceedings of the International Conference on Information Systems Orlando, USA, 2012.
[7] D. Arnott, G. Pervan, A critical analysis of decision support systems research, Journal of Information Technology, 20 (2005) 67-87.
[8] R. Sharma, S. Mithas, A. Kankanhalli, Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations, European Journal of Information Systems, 23 (2014) 433-441.
[9] M. Bidan, F. Rowe, D. Truex, An empirical study of IS architectures in French SMEs: integration approaches, European Journal of Information Systems, 21 (2012).
[10] E. Turban, R. Sharda, D. Delen, Decision Support and Business Intelligence Systems, Pearson, New Jersey, 2011.
[11] X. Deng, L. Chi, Understanding Postadoptive Behaviors in Information Systems Use: A Longitudinal Analysis of System Use Problems in the Business Intelligence Context, Journal of Management Information Systems, 29 (2012) 291-326.
[12] C. Soh, M.L. Markus, How IT creates business value: a process theory synthesis, Proceedings of the International Conference on Information Systems Amsterdam, Netherlands, 1995, pp. 29-41.
[13] N. Melville, K. Kraemer, V. Gurbaxani, Review: Information technology and organizational performance: An integrative model of IT business value, MIS Quarterly, 28 (2004) 283-322.
[14] G. Schryen, Revisiting IS business value research: what we already know, what we still need to know, and how we can get there, European Journal of Information Systems, 22 (2013) 139-169.
[15] D. Robey, G. Im, J.D. Wareham, Theoretical foundations of empirical research on interorganizational systems: assessing past contributions and guiding future directions, Journal of the Association for Information Systems, 9 (2008) 4.
[16] S.S. Li, E. Karahanna, Online Recommendation Systems in a B2C E-Commerce Context: A Review and Future Directions, Journal of the Association for Information Systems, 16 (2015) 72-107.
[17] T. Tamm, P.B. Seddon, G. Shanks, P. Reynolds, How Does Enterprise Architecture Add Value to Organisations?, Communications of the Association for Information Systems, 28 (2011) 10.
[18] C. Li, X.S. Wang, A data model for supporting on-line analytical processing, Proceedings of the fifth international conference on Information and Knowledge Management, ACM, 1996, pp. 81-88.
[19] A. Cuzzocrea, I.-Y. Song, K.C. Davis, Analytics over large-scale multidimensional data: the big data revolution!, Proceedings of the ACM 14th international workshop on Data Warehousing and OLAP, ACM, 2011, pp. 101-104.
[20] F. Rowe, What literature review is not: diversity, boundaries and recommendations, European Journal of Information Systems, 23 (2014) 241-255.
[21] R. Kohli, V. Grover, Business value of IT: An essay on expanding research directions to keep up with the times, Journal of the Association for Information Systems, 9 (2008) 23-39.
[22] B. Dehning, V.J. Richardson, Returns on investments in information technology: A research synthesis, Journal of Information Systems, 16 (2002) 7-30.
[23] J. Dedrick, V. Gurbaxani, K.L. Kraemer, Information technology and economic performance: A critical review of the empirical evidence, ACM Computing Surveys (CSUR), 35 (2003) 1-28.
[24] M.L. Markus, D. Robey, Information technology and organizational change: causal structure in theory and research, Management Science, 34 (1988) 583-598.

[25] G. Schryen, G. Wagner, A. Benlian, Theory of knowledge for literature reviews: an epistemological model, taxonomy and empirical analysis of IS literature, Proceedings of the 36th International Conference on Information Systems, Fort Worth, TX, 2015, pp. 1-22.
[26] T.-O. Salge, R. Kohli, M. Barrett, Investing in Information Systems: On the Behavioral and Institutional Search Mechanisms Underpinning Hospitals' IS Investment Decisions, MIS Quarterly, 39 (2015) 61-89.
[27] R. Sabherwal, A. Jeyaraj, Information technology impacts on firm performance: an extension of Kohli and Devaraj (2003), MIS Quarterly, 39 (2015) 809-836.
[28] P.B. Seddon, S. Staples, R. Patnayakuni, M. Bowtell, Dimensions of information systems success, Communications of the AIS, 2 (1999).
[29] V.R. Prybutok, L.A. Kappelman, B.L. Myers, A comprehensive model for assessing the quality and productivity of the information systems function: toward a theory for information systems assessment, Information Resources Management Journal, 10 (1997) 6-26.
[30] G. Schryen, Writing qualitative IS literature reviews–Guidelines for synthesis, interpretation and guidance of research, Communications of the Association for Information Systems, 37 (2014).
[31] S. Devaraj, R. Kohli, Information technology payoff in the health-care industry: a longitudinal study, Journal of Management Information Systems, 16 (2000) 41-67.
[32] C.M. Cheung, D.R. Thadani, The impact of electronic word-of-mouth communication: A literature analysis and integrative model, Decision Support Systems, 54 (2012) 461-470.
[33] A. Burton-Jones, What have we learned from the Smart Machine?, Information and Organization, 24 (2014) 71-105.
[34] M. Barrett, G. Walsham, Making contributions from interpretive case studies: Examining processes of construction and use, Information Systems Research, Springer 2004, pp. 293-312.
[35] T.D. Clark, M.C. Jones, C.P. Armstrong, The dynamic structure of management support systems: theory development, research focus, and direction, MIS Quarterly, 31 (2007) 579-615.
[36] B. Dinter, Success factors for information logistics strategy — An empirical investigation, Decision Support Systems, 54 (2013) 1207-1218.
[37] J.R. Landis, G.G. Koch, The measurement of observer agreement for categorical data, Biometrics, 33 (1977) 159-174.
[38] C.-W. Tan, I. Benbasat, R.T. Cenfetelli, IT-mediated customer service content and delivery in electronic governments: An empirical investigation of the antecedents of service quality, MIS quarterly, 37 (2013) 77-109.
[39] J. Hagerty, R.L. Sallam, J. Richardson, Magic quadrant for business intelligence platforms, Gartner for Business Leaders (February 6, 2012), 2012.
[40] J. Luftman, H.S. Zadeh, B. Derksen, M. Santana, E.H. Rigoni, Z. Huang, Key information technology and management issues 2011-2012: an international study, Journal of Information Technology, 27 (2012) 198-212.
[41] M. Benaroch, M. Jeffery, R.J. Kauffman, S. Shah, Option-Based Risk Management: A Field Study of Sequential Information Technology Investment Decisions, Journal of Management Information Systems, 24 (2007) 103-140.
[42] S.-H. Park, S.-Y. Huh, W. Oh, S.P. Han, A Social Network-Based Inference Model for Validating Customer Profile Data, MIS Quarterly, 36 (2012) 1217-1237.
[43] J.H. Lee, S.C. Park, Intelligent profitable customers segmentation system based on business intelligence tools, Expert Systems with Applications, 29 (2005) 145-152.
[44] G.J. Hahn, J. Packowski, A perspective on applications of in-memory analytics in supply chain management, Decision Support Systems, 76 (2015) 45-52.
[45] P. Trkman, K. McCormack, M.P.V. de Oliveira, M.B. Ladeira, The impact of business analytics on supply chain performance, Decision Support Systems, 49 (2010) 318-327.
[46] J. Baker, D.R. Jones, J. Burkman, Using Visual Representations of Data to Enhance Sensemaking in Data Exploration Tasks, Journal of the Association for Information Systems, 10 (2009) 533-559.
[47] W.F. Cody, J.T. Kreulen, V. Krishna, W.S. Spangler, The integration of business intelligence and knowledge management, IBM Systems Journal, 41 (2002) 697-713.
[48] D. Roussinov, M. Chau, Combining Information Seeking Services into a Meta Supply Chain of Facts Journal of the Association for Information Systems, 9 (2008) 175-199.

[49] J.H. Heinrichs, J.-S. Lim, Integrating web-based data mining tools with business models for knowledge management, Decision Support Systems, 35 (2003) 103-112.
[50] W. Chung, H. Chen, J.F. Nunamaker Jr, A visual framework for knowledge discovery on the web: An empirical study of business intelligence exploration, Journal of Management Information Systems, 21 (2005) 57-84.
[51] M. Petrini, M. Pozzebon, Managing sustainability with the support of business intelligence: Integrating socio-environmental indicators and organisational context, The Journal of Strategic Information Systems, 18 (2009) 178-191.
[52] F. Borrajo, Y. Bueno, I. de Pablo, B. Santos, F. Fernández, J. García, I. Sagredo, SIMBA: A simulator for business education and research, Decision Support Systems, 48 (2010) 498-506.
[53] H. Demirkan, D. Delen, Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud, Decision Support Systems, 55 (2013) 412-421.
[54] C. Francalanci, V. Morabito, IS integration and business performance: The mediation effect of organizational absorptive capacity in SMEs, Journal of Information Technology, 23 (2008) 297-312.
[55] B.L. Cooper, H.J. Watson, B.H. Wixom, D.L. Goodhue, Data Warehousing Supports Corporate Strategy at First American Corporation, MIS Quarterly, 24 (2000) 547-567.
[56] H.J. Watson, C. Fuller, T. Ariyachandra, Data warehouse governance: best practices at Blue Cross and Blue Shield of North Carolina, Decision Support Systems, 38 (2004) 435-450.
[57] S.C. Park, S. Piramuthu, M.J. Shaw, Dynamic rule refinement in knowledge-based data mining systems, Decision Support Systems, 31 (2001) 205-222.
[58] J.E. Frisk, R. Lindgren, L. Mathiassen, Design matters for decision makers: Discovering IT investment alternatives, European Journal of Information Systems, 23 (2014) 442-461.
[59] A. Counihan, P. Finnegan, D. Sammon, Towards a framework for evaluating investments in data warehousing, Information Systems Journal, 12 (2002) 321-338.
[60] M. Ko, K.-M. Osei-Bryson, Using regression splines to assess the impact of information technology investments on productivity in the health care industry, Information Systems Journal, 14 (2004) 43-63.
[61] K. Ramamurthy, A. Sen, A.P. Sinha, An empirical investigation of the key determinants of data warehouse adoption, Decision Support Systems, 44 (2008) 817-841.
[62] M.Z. Elbashir, P.A. Collier, M.J. Davern, Measuring the effects of business intelligence systems: The relationship between business process and organizational performance, International Journal of Accounting Information Systems, 9 (2008) 135-153.
[63] B.H. Wixom, H.J. Watson, An empirical investigation of the factors affecting data warehousing success, MIS Quarterly, 25 (2001) 17-32.
[64] J. Ang, T.S.H. Teo, Management issues in data warehousing: insights from the Housing and Development Board, Decision Support Systems, 29 (2000) 11-20.
[65] T. Ariyachandra, H. Watson, Key organizational factors in data warehouse architecture selection, Decision Support Systems, 49 (2010) 200-212.
[66] W. Fan, H. Lu, S.E. Madnick, D. Cheung, DIRECT: a system for mining data value conversion rules from disparate data sources, Decision Support Systems, 34 (2002) 19-39.
[67] J. Jiao, L. Zhang, S. Pokharel, Z. He, Identifying generic routings for product families based on text mining and tree matching, Decision Support Systems, 43 (2007) 866-883.
[68] B. Chae, A complexity theory approach to IT-enabled services (IESs) and service innovation: Business analytics as an illustration of IES, Decision Support Systems, 57 (2014) 1-10.
[69] P.P. Tallon, R.V. Ramirez, J.E. Short, The Information Artifact in IT Governance: Toward a Theory of Information Governance, Journal of Management Information Systems, 30 (2013) 141-178.
[70] U. Schultze, A Confessional Account Of An Ethnography About Knowledge Work, MIS Quarterly, 24 (2000) 3-41.
[71] R.R. Nelson, P.A. Todd, B.H. Wixom, Antecedents of information and system quality: an empirical examination within the context of data warehousing, Journal of Management Information Systems, 21 (2005) 199-235.
[72] M.Z. Elbashir, P.A. Collier, S.G. Sutton, The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems, Accounting Review, 86 (2011) 155-184.

[73] T. Ramakrishnan, M.C. Jones, A. Sidorova, Factors influencing business intelligence (BI) data collection strategies: An empirical investigation, Decision Support Systems, 52 (2012) 486-496.
[74] J. Luftman, H.S. Zadeh, Key information technology and management issues 2010-11: an international study, Journal of Information Technology, 26 (2011) 193-204.
[75] G. Kou, X. Liu, Y. Peng, Y. Shi, M. Wise, W. Xu, Multiple criteria linear programming approach to data mining: Models, algorithm designs and software development, Optimization Methods and Software, 18 (2003) 453-473.
[76] G. Pant, P. Srinivasan, Predicting Web Page Status, Information Systems Research, 21 (2010) 345-364,410-411.
[77] H. Watson, B.H. Wixom, J.A. Hoffer, R. Anderson-Lehman, A.M. Reynolds, Real-time business intelligence: Best practices at continental airlines, Information Systems Management, 23 (2006) 7-18.
[78] M. Chau, J. Xu, Business Intelligence in Blogs: Understanding Consumer Interactions and Communities, MIS Quarterly, 36 (2012).
[79] R.Y. Lau, S.S. Liao, K.-F. Wong, D.K. Chiu, Web 2.0 Environmental Scanning and Adaptive Decision Support for Business Mergers and Acquisitions, MIS Quarterly, 36 (2012) 1239-1268.
[80] D. Hu, J.L. Zhao, Z. Hua, M.C.S. Wong, Network-based modeling and analysis of systemic risk in banking systems, MIS Quarterly, 36 (2012) 1269-1291.
[81] A. Abbasi, C. Albrecht, A. Vance, J. Hansen, MetaFraud: A Meta-Learning Framework for Detecting Financial Fraud, MIS Quarterly, 36 (2012) 1293-1327.
[82] N. Sahoo, P.V. Singh, T. Mukhopadhyay, A hidden Markov model for collaborative filtering, MIS Quarterly, 36 (2012) 1329-1356.
[83] N. Di Domenica, G. Mitra, P. Valente, G. Birbilis, Stochastic programming and scenario generation within a simulation framework: An information systems perspective, Decision Support Systems, 42 (2007) 2197-2218.
[84] J. Lee, M. Podlaseck, E. Schonberg, R. Hoch, Visualization and analysis of clickstream data of online stores for understanding web merchandising, Data Mining and Knowledge Discovery, 5 (2001) 59-84.
[85] K. Rouibah, S. Ould-ali, PUZZLE: a concept and prototype for linking business intelligence to business strategy, The Journal of Strategic Information Systems, 11 (2002) 133-152.
[86] A.S. Abrahams, J. Jiao, G.A. Wang, W. Fan, Vehicle defect discovery from social media, Decision Support Systems, 54 (2012) 87-97.
[87] D.L. Olson, D. Delen, Y. Meng, Comparative analysis of data mining methods for bankruptcy prediction, Decision Support Systems, 52 (2012) 464-473.
[88] Á. García-crespo, R. Colomo-palacios, J.M. Gómez-berbís, B. Ruiz-mezcua, SEMO: a framework for customer social networks analysis based on semantics, Journal of Information Technology, 25 (2010) 178-188.
[89] M. Zorrilla, D. García-Saiz, A service oriented architecture to provide data mining services for non-expert data miners, Decision Support Systems, 55 (2013) 399-411.
[90] A.P. Sinha, H. Zhao, Incorporating domain knowledge into data mining classifiers: An application in indirect lending, Decision Support Systems, 46 (2008) 287-299.
[91] Y. Shi, Y. Peng, G. Kou, Z. Chen, Classifying credit card accounts for business intelligence and decision making: A Multiple-criteria quadratic programming approach, International Journal of Information Technology and Decision Making, 4 (2005) 581-599.
[92] F. Weiguo, M.D. Gordon, P. Pathak, Genetic Programming-Based Discovery of Ranking Functions for Effective Web Search, Journal of Management Information Systems, 21 (2005) 37-56.
[93] Z. Zheng, P. Fader, B. Padmanabhan, From Business Intelligence to Competitive Intelligence: Inferring Competitive Measures Using Augmented Site-Centric Data, Information Systems Research, 23 (2012) 698-720.
[94] Y. Peng, Y. Zhang, Y. Tang, S. Li, An incident information management framework based on data integration, data mining, and multi-criteria decision making, Decision Support Systems, 51 (2011) 316-327.
[95] B. Padmanabhan, Z. Zhiqiang, S.O. Kimbrough, An Empirical Analysis of The Value Of Complete Information for ECRM Models, MIS Quarterly, 30 (2006) 247-267.
[96] H. Wang, S. Wang, A knowledge management approach to data mining process for business intelligence, Industrial Management and Data Systems, 108 (2008) 622-634.

[97] C. Speier, M.G. Morris, The Influence of Query Interface Design on Decision-Making Performance, MIS Quarterly, 27 (2003) 397-423.
[98] H. Lee, Y. Lee, H. Cho, K. Im, Y.S. Kim, Mining churning behaviors and developing retention strategies based on a partial least squares (PLS) model, Decision Support Systems, 52 (2011) 207-216.
[99] V. Choudhary, J. Vithayathil, The Impact of Cloud Computing: Should the IT Department Be Organized as a Cost Center or a Profit Center?, Journal of Management Information Systems, 30 (2013) 67-100.
[100] S. Spangler, J.T. Kreulen, J. Lessler, Generating and Browsing Multiple Taxonomies Over a Document Collection, Journal of Management Information Systems, 19 (2003) 191-212.
[101] C.-H. Chou, A.P. Sinha, H. Zhao, A Hybrid Attribute Selection Approach for Text Classification, Journal of the Association for Information Systems, 11 (2010) 491-519.
[102] D.J. Berndt, J.W. Fisher, J.G. Craighead, A.R. Hevner, S. Luther, J. Studnicki, The role of data warehousing in bioterrorism surveillance, Decision Support Systems, 43 (2007) 1383-1403.
[103] A.N.K. Chen, P.B. Goes, J.R. Marsden, A Query-Driven Approach to the Design and Management of Flexible Database Systems, Journal of Management Information Systems, 19 (2002) 121-154.
[104] Y.-L. Chen, J.-M. Chen, C.-W. Tung, A data mining approach for retail knowledge discovery with consideration of the effect of shelf-space adjacency on sales, Decision Support Systems, 42 (2006) 1503-1520.
[105] W. Chung, A. Bonillas, G. Lai, W. Xi, H. Chen, Supporting non-English Web searching: An experiment on the Spanish business and the Arabic medical intelligence portals, Decision Support Systems, 42 (2006) 1697-1714.
[106] L. Churilov, A. Bagirov, D. Schwartz, K. Smith, M. Dally, Data Mining with Combined Use of Optimization Techniques and Self-Organizing Maps for Improving Risk Grouping Rules: Application to Prostate Cancer Patients, Journal of Management Information Systems, 21 (2005) 85-100.
[107] S. De Cnudde, D. Martens, Loyal to your city? A data mining analysis of a public service loyalty program, Decision Support Systems, 73 (2015) 74-84.
[108] M.Y. Kiang, A. Kumar, An evaluation of self-organizing map networks as a robust alternative to factor analysis in data mining applications, Information Systems Research, 12 (2001) 177-194.
[109] Y. Kim, W.N. Street, An intelligent system for customer targeting: a data mining approach, Decision Support Systems, 37 (2004) 215-228.
[110] F.-r. Lin, K.-j. Huang, N.-s. Chen, Integrating information retrieval and data mining to discover project team coordination patterns, Decision Support Systems, 42 (2006) 745-758.
[111] H. Liu, F. Lin, J. He, Y. Cai, New approach for the sequential pattern mining of high-dimensional sequence databases, Decision Support Systems, 50 (2010) 270-280.
[112] D. Martens, L. Bruynseels, B. Baesens, M. Willekens, J. Vanthienen, Predicting going concern opinion with data mining, Decision Support Systems, 45 (2008) 765-777.
[113] P. Ravisankar, V. Ravi, G. Raghava Rao, I. Bose, Detection of financial statement fraud and feature selection using data mining techniques, Decision Support Systems, 50 (2011) 491-500.
[114] M.L. Wong, S.Y. Lee, K.S. Leung, Data mining of Bayesian networks using cooperative coevolution, Decision Support Systems, 38 (2004) 451-472.
[115] X.-B. Li, S. Sarkar, Privacy Protection in Data Mining: A Perturbation Approach for Categorical Data, Information Systems Research, 17 (2006) 254-270,321-322.
[116] X.-B. Li, S. Sarkar, Digression and Value Concatenation to Enable Privacy-Preserving Regression, MIS Quarterly, 38 (2014) 679-698.
[117] D. Zhu, X.-B. Li, S. Wu, Identity disclosure protection: A data reconstruction approach for privacy-preserving data mining, Decision Support Systems, 48 (2009) 133-140.
[118] D. Guo, Visual analytics of spatial interaction patterns for pandemic decision support, International Journal of Geographical Information Science, 21 (2007) 859-877.
[119] K. Verbert, N. Manouselis, H. Drachsler, E. Duval, Dataset-driven research to support learning and knowledge analytics, Educational Technology and Society, 15 (2012) 133-148.
[120] H. Wu, M. Gordon, K. DeMaagd, W. Fan, Mining web navigations for intelligence, Decision Support Systems, 41 (2006) 574-591.

[121] J. Collins, W. Ketter, M. Gini, Flexible decision support in dynamic inter-organisational networks, European Journal of Information Systems, 19 (2010) 436-448.
[122] E. Fernández-Medina, J. Trujillo, M. Piattini, Model-driven multidimensional modeling of secure data warehouses, European Journal of Information Systems, 16 (2007) 374-389.
[123] A. Popovič, R. Hackney, P.S. Coelho, J. Jaklič, Towards business intelligence systems success: Effects of maturity and culture on analytical decision making, Decision Support Systems, 54 (2012) 729-739.
[124] D. Martens, F. Provost, Explaining Data-Driven Document Classifications, MIS Quarterly, 38 (2014) 73-99.
[125] H. Thomas, A. Datta, A conceptual model and algebra for on-line analytical processing in decision support databases, Information Systems Research, 12 (2001) 83-102.
[126] W. Chung, Y. Zhang, Z. Huang, G. Wang, T.H. Ong, H. Chen, Internet searching and browsing in a multilingual world: An experiment on the Chinese business intelligence portal (CBizPort), Journal of the American Society for Information Science and Technology, 55 (2004) 818-831.
[127] G. Bansal, A.P. Sinha, H. Zhao, Tuning Data Mining Methods for Cost-Sensitive Regression: A Study in Loan Charge-Off Forecasting, Journal of Management Information Systems, 25 (2008) 315-336.
[128] G. Shmueli, O.R. Koppius, Predictive Analytics in Information Systems Research, MIS Quarterly, 35 (2011) 553-572.
[129] F.S.C. Tseng, A.Y.H. Chou, The concept of document warehousing for multi-dimensional modeling of textual-based business intelligence, Decision Support Systems, 42 (2006) 727-744.
[130] D. Vujošević, I. Kovačević, M. Suknović, N. Lalić, A comparison of the usability of performing ad hoc querying on dimensionally modeled data versus operationally modeled data, Decision Support Systems, 54 (2012) 185-197.
[131] H. Wang, Q. Wei, G. Chen, From clicking to consideration: A business intelligence approach to estimating consumers' consideration probabilities, Decision Support Systems, 56 (2013) 397-405.
[132] S. Bhattacharyya, S. Jha, K. Tharakunnel, J.C. Westland, Data mining for credit card fraud: A comparative study, Decision Support Systems, 50 (2011) 602-613.
[133] R. Garg, M.D. Smith, R. Telang, Measuring Information Diffusion in an Online Community, Journal of Management Information Systems, 28 (2011) 11-38.
[134] A. Popovič, R. Hackney, P.S. Coelho, J. Jaklič, How information-sharing values influence the use of information systems: An investigation in the business intelligence systems context, The Journal of Strategic Information Systems, 23 (2014) 270-283.
[135] Y. Chen, K. Ramamurthy, K.-W. Wen, Organizations' Information Security Policy Compliance: Stick or Carrot Approach?, Journal of Management Information Systems, 29 (2012) 157-188.
[136] X. Li, J.J.P.-A. Hsieh, A. Rai, Motivational Differences Across Post-Acceptance Information System Usage Behaviors: An Investigation in the Business Intelligence Systems Context, Information Systems Research, 24 (2013) 659-682.
[137] G. Meyer, G. Adomavicius, P.E. Johnson, M. Elidrisi, W.A. Rush, J.M. Sperl-Hillen, P.J. O'Connor, A Machine Learning Approach to Improving Dynamic Decision Making, Information Systems Research, 25 (2014) 239-263,437-440.
[138] H. Watson, B.H. Wixom, The current state of business intelligence, Computer, 40 (2007) 96-99.
[139] S.L. Jarvenpaa, D.E. Leidner, An information company in Mexico: Extending the resource-based view of the firm to a developing country context, Information Systems Research, 9 (1998) 342-361.
[140] E. Brynjolfsson, L.M. Hitt, Beyond the productivity paradox, Communications of the ACM, 41 (1998) 49-55.
[141] R. Sharma, P. Reynolds, R. Scheepers, P.B. Seddon, G.G. Shanks, Business Analytics and Competitive Advantage: A Review and a Research Agenda, DSS, 2010, pp. 187-198.
[142] R.L. Purvis, V. Sambamurthy, R.W. Zmud, The assimilation of knowledge platforms in organizations: An empirical investigation, Organization Science, 12 (2001) 117-135.
[143] J.W. Ross, C.M. Beath, D.L. Goodhue, Develop long-term competitiveness through IT assets, Sloan Management Review, 38 (1996) 31-42.
[144] A. Burton-Jones, C. Grange, From Use to Effective Use: A Representation Theory Perspective, Information Systems Research, 24 (2013) 632-658.

[145] W.J. Orlikowski, Using technology and constituting structures: A practice lens for studying technology in organizations, Organization Science, 11 (2000) 404-428.
[146] A.W. Trice, M.E. Treacy, Utilization as a dependent variable in MIS research, ACM SIGMIS Database, 19 (1988) 33-41.
[147] P.B. Seddon, A respecification and extension of the DeLone and McLean model of IS success, Information Systems Research, 8 (1997) 240-253.
[148] R. Santhanam, E. Hartono, Issues in linking information technology capability to firm performance, MIS Quarterly, 27 (2003) 125-153.
[149] R. Hackathorn, The BI Watch Real-Time to Real-Value, DM review, 14 (2004) 24-29.
[150] R.v.d. Meulen, J. Rivera, Gartner Predicts Business Intelligence and Analytics Will Remain Top Focus for CIOs Through 2017, Gartner, 2013.
[151] L. Goasduff, C. Pettey, Gartner Says New Relationships Will Change Business Intelligence and Analytics, Gartner, 2011.
[152] Z. Wan, Y. Fang, M. Wade, A ten-year odyssey of the'IS productivity paradox'-A citation analysis (1996-2006), AMCIS 2007 Proceedings, 2007, pp. 437.
[153] F. Bélanger, M. Cefaratti, T. Carte, S.E. Markham, Multilevel research in information systems: Concepts, strategies, problems, and pitfalls, Journal of the Association for Information Systems, 15 (2014) 614.
[154] D.G. Sirmon, M.A. Hitt, R.D. Ireland, B.A. Gilbert, Resource orchestration to create competitive advantage breadth, depth, and life cycle effects, Journal of Management, 37 (2011) 1390-1412.
[155] B. Wernerfelt, A resource-based view of the firm, Strategic management journal, 5 (1984) 171-180.
[156] D. Robey, Computer information systems and organization structure, Communications of the ACM, 24 (1981) 679-687.
[157] H.R. Greve, Interorganiational evolution, in: J.A.C. Baum (Ed.) Companion to Organizations, The Blackwell, Oxford, UK, 2002, pp. 957.
[158] G. Walsham, Cross-cultural software production and use: a structurational analysis, MIS quarterly, 26 (2002) 359-380.
[159] W. Cho, M.J. Shaw, Does IT Synergy Matter in IT Portfolio Selection?, Proceedings of the International Conference on Information Systems Phoenix, Arizona, USA, 2009, pp. 160.
[160] L. Fink, N. Yogev, A. Even, Business Intelligence and Organizational Learning: An Empirical Investigation of Value Creation Processes, Information & Management, DOI (2016).
[161] A. Burton-Jones, E.R. McLean, E. Monod, Theoretical perspectives in IS research: from variance and process to conceptual latitude and conceptual fit, European Journal of Information Systems, 24 (2015) 664-679.
[162] J.W. Ross, Enterprise Architecture: Driving business benefits from IT, MIT Sloan School of Management Center for Information Systems Research (CISR), 2006.
[163] G. DeSanctis, M.S. Poole, Capturing the complexity in advanced technology use: Adaptive structuration theory, Organization Science, 5 (1994) 121-147.
[164] W.W. Chin, A. Gopal, W.D. Salisbury, Advancing the theory of adaptive structuration: The development of a scale to measure faithfulness of appropriation, Information Systems Research, 8 (1997) 342-367.
[165] A. Mills, W. Chin, Conceptualizing creative use: an examination of the construct and its determinants, AMCIS 2007 proceedings, Keystone, Colorado, 2007, pp. 289.
[166] H. Watson, Tutorial: Big data analytics: Concepts, technologies, and applications, Communications of the Association for Information Systems, 34 (2014) 1247-1268.
[167] J.A.C. Baum, T.L. Amburgrey, Organizational Ecology, in: J.A.C. Baum (Ed.) Companion to Organizations, Blackwell, Oxford, UK, 2002, pp. 957.
[168] D.J. Koys, The effects of employee satisfaction, organizational citizenship behavior, and turnover on organizational effectiveness: A unit-level, longitudinal study, Personnel Psychology, 54 (2001) 101-114.
[169] L.-Y. Sun, S. Aryee, K.S. Law, High-performance human resource practices, citizenship behavior, and organizational performance: A relational perspective, Academy of Management Journal, 50 (2007) 558-577.

Highlights

- How do organizations obtain value from BI systems?
- Comprehensive review of BI literature from 1/2000-8/2015
- Mapped literature findings to integrated framework of BI value
- Results show the field's knowledge of the necessary conditions for obtaining value
- Results show the field's lack of knowledge of the processes for obtaining value