Business Intelligence and Analytics in Small and Medium-Sized Enterprises

Marilex Rea Llave

UiA University of Agder

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Evaluation Committee

Jos van Hillegersberg, Professor
University of Twente, Netherlands

Anne Mette Fuglseth, Professor
NHH Norwegian School of Economics, Norway

Bjørn Erik Munkvold, Professor
University of Agder, Norway

Supervisors

Dag H. Olsen, Professor
University of Agder, Norway

Eli Hustad, Professor
University of Agder, Norway

This thesis is dedicated to

my beloved late father, Alexander Sacramento Llave

and my beloved mother, Celia Rea Llave.

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List of Abbreviations

BA	Business Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
CRM	Customer Relationship Management
CSF	Critical Success Factor
DBMS	Database Management System
D&M	DeLone and McLean
DOI	Diffusion of Innovation Theory
DSS	Decision Support System
DW	Data Warehouse
EIS	Executive Information System
ERP	Enterprise Resource Planning
ETL	Extract-Transform-Load
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
KM	Knowledge Management
KPI	Key Performance Indicator
MIS	Management Information System
PDSS	Personal Decision Support System
RBV	Resource-Based View
SaaS	Software-as-a-Service
SCA	Supply Chain Analytics
SCM	Supply Chain Management
SME	Small and Medium-Sized Enterprise
TAM	Technology Acceptance Model
TOE	Technology, Organization, and Environment
UTAUT	Unified Theory of Acceptance and Use of Technology
VRIN	Valuable, Rareness, Inimitable, and Non-substitutable

Abstract

This thesis presents a study of Business Intelligence and Analytics (BI&A) adoption in small and medium-sized enterprises (SMEs). Although the importance of BI&A is widely accepted, empirical research shows SMEs still lag in BI&A proliferation. Thus, it is crucial to understand the phenomenon of BI&A adoption in SMEs.

This thesis will investigate and explore BI&A adoption in SMEs, addressing the main research question: *How can we understand the phenomenon of BI&A adoption in SMEs?* The adoption term in this thesis refers to all the IS adoption stages, including investment, implementation, utilization, and value creation. This research uses a combination of a literature review, a qualitive exploratory approach, and a ranking-type Delphi study with a grounded Delphi approach. The empirical part includes interviews with 38 experts and Delphi surveys with 39 experts from various Norwegian industries.

The research strategy investigates the factors influencing BI&A adoption in SMEs. The study examined the investment, implementation, utilization, and value creation of BI&A technologies in SMEs. A thematic analysis was adopted to collate the qualitative expert interview data and search for potential themes. The Delphi survey findings were further examined using the grounded Delphi method. To better understand the study's findings, three theoretical perspectives were applied: resource-based view theory, dynamic capabilities, and IS value process models.

The thesis' research findings are presented in five articles published in international conference proceedings and journals. This thesis summary will coherently integrate and discuss these results.

The thesis makes five contributions. First, it provides an overview of BI&A adoption in SMEs by synthesizing extant research contributions on this topic. Second, the study contributes to the research stream on BI&A adoption in SMEs by identifying the core drivers and inhibitors, focusing on the lack of resources to explain the slow adoption or non-adoption of BI&A. Third, the study demonstrates how BI&A helps generate business value. Fourth, the thesis suggests an iterative and gradual approach as preferable for SMEs and proposes a revised IS value process model to represent the iterative and dynamic nature of BI&A. Finally, the study illustrates the combination of the three theoretical perspectives, which contributes to a better understanding of the findings. In addition, this thesis presents a set of recommendations to help SMEs achieve successful BI&A adoption and value creation. Furthermore, the combination of a ranking-type Delphi study with a grounded Delphi approach and exploratory qualitative expert interviews offers a rigorous methodological approach to gain a deeper understanding of BI&A adoption in SMEs.

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I am a great believer in luck. The harder I work, the more of it I seem to have.

— *Coleman Cox.*

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1 Introduction

Business intelligence and analytics (BI&A) are data-centric approaches complementing data with a set of methodologies, processes, technologies, and tools to analyze and extract information from data (Lim et al., 2013). BI&A offers a way for businesses to examine their data to enhance decision-making, understand trends, and unearth valuable insights (Gürdür et al., 2019). It has evolved from data warehousing with a focus on static reporting focus on intelligence (Simmers, 2004). At the same time, it also shifts from a data transformation function into a function of information as the focal point of the current function of data transformation into intelligence. BI&A leverages software and services to transform data into actionable intelligence informing an organization's strategic and tactical business decisions. With BI&A, businesses can access and analyze data sets and present analytical findings in reports, summaries, dashboards, graphs, charts, and maps to provide users with detailed intelligence of the business's state. In short, BI&A is an information system supporting decision-making processes by helping organizations discover new knowledge, offer analysis solutions, ad hoc queries, reporting, and forecasting (Yoon et al., 2014).

Globalization, the internationalization of markets, the knowledge economy, and e-commerce are some numerous challenges facing all organizations, regardless of size. If organizations will survive and be competitive in their new environment, they must use information systems (IS) and information technologies (IT) (Poba-Nzaou et al., 2008). Successful organizations are differentiated by their ability to make accurate, timely, and effective decisions at all levels to address their customers' preferences and priorities (Bose, 2009).

The importance of small and medium-sized enterprises (SMEs) worldwide is indisputable. The definition of SMEs varies across nations; most denominators are employment figures, turnover, and investments and fixed assets (Costello et al., 2007). This thesis follows the definition of SMEs according to the European Commission. SMEs are enterprises with fewer than 250 employees and have an annual turnover not exceeding 50 million euro, which is 99% of all European firms (IFC, 2012, p. 1). SMEs balance both political and economic independence and drive diversified socio-economic infrastructures in the form of employment creation, flexibility, and innovations (Dwivedi et al. 2009). Therefore, SMEs are the bedrock for industrialization.

Unlike large enterprises, SMEs schedule a limited budget and organizational change (Ruivo et al., 2015), limited resources, limited expertise, and limited impact on their environment (Carson et al., 1995). Traditionally, SMEs are slow adopters of IS/IT (Raymond, 1988) due to scarce resources, small budgets, and limited technical expertise. This creates potential barriers preventing them from adopting innovative technologies to improve organizational performance (Levy and Powell, 2000). The two most important inhibitors to IS/IT progress in SMEs are financial obstacles and lack of technical knowledge (Iacovou et al., 1995). However, SMEs can be more responsive to dynamic environments and more susceptible to digital innovations than larger enterprises (Chan et al., 2019) because of their informal structures. According to the literature, the problems, opportunities, and management issues encountered by SMEs in IS adoption area are unique (Premkumar, 2003). In addition, their resources, capabilities, and business processes are idiosyncratic in nature. Therefore, adopting BI&A in SMEs likely has different drivers and inhibitors than larger enterprises.

Traditionally, the need for BI&A-driven insights might be more pronounced in companies dealing with large amounts of information. Today, many small-scale companies generate a lot of data. Data generation depends on its business model rather than firm size. Many business owners and managers are bombarded with information overload and urgently seek ways to derive greater control, understanding, and intelligence from organizational data. Thus, SMEs and entrepreneurs also need to make data-driven decisions.

Compared to large enterprises, they lag behind in utilizing the BI&A potential (Baransel and Baransel, 2012). A BI&A initiative is not a task free from risks, nor does it automatically achieve improved performance. Therefore, both practitioners and researchers must understand the factors influencing BI&A adoption to ensure BI&A success (Cruz-Jesus et al., 2018). Previous studies failed to present convincing empirical evidence of BI&A adoption in SME. Despite BI&A's significance, relatively little empirical research has directly addressed the deeper understanding of factors influencing SME adoption processes. The business value generation process associated with adopting these technologies is still unclear (Moreno et al., 2018, Trieu, 2017).

Given the above motivations, this thesis aims to increase the understanding of BI&A adoption in SMEs and how SMEs create value from BI&A initiatives. To gain a better understanding, this overarching research question is investigated: *How can we understand the phenomenon of BI&A adoption in SMEs?* This thesis interprets IS adoption in these stages: investment, implementation, utilization, and value creation from BI&A initiatives. To better understand BI&A adoption, I specifically investigated the following research sub-questions:

SQ1: What are the drivers and inhibitors of BI&A adoption in SMEs?
SQ2: How are BI&A utilized and implemented in SMEs?
SQ3: How do SMEs create value from BI&A initiatives?

I will answer the above questions by eliciting knowledge from BI&A experts in Norwegian industries. The empirical basis for the thesis is a ranking-type Delphi study with a grounded Delphi approach and exploratory study using qualitative expert interview technique. The results of this study are presented and discussed in five research publications (Appendix B). This thesis summary will integrate the research publications and present the research findings coherently.

The rest of this thesis is structured as follows: Chapter 2 presents the three applied theoretical perspectives. Chapter 3 introduces the literature of BI&A, SME context, and IS adoption. Chapter 4 describes the applied research approach, including the research design, gaining informants, data collection, data analysis, and validity issues. Chapter 5 views the five research publications by summarizing each research paper and their findings. Chapter 6 presents the thesis contributions. Chapter 7 has a thesis summary, research limitation highlights, and future research suggestions.

2 Theoretical Background

This chapter will discuss the theoretical lenses applied to understand the study's findings. Chapter 2.1 introduces the resource-based view of the firm developed to understand how organizations achieve sustainable competitive advantages through their resources and capabilities. The dynamic capabilities theory focuses on how organizations develop and renew their resources and capabilities to adapt to environmental changes and is presented in Chapter 2.2. Finally, Chapter 2.3 introduces the IS value process model to help explain how and why IS investments may lead to improved organizational performance.

2.1 The Resource-Based View

The resource-based view (RBV) traditionally emphasizes the role of resources and capabilities as fundamental sources of firm-level value creation (Barney, 1991). RBV theorizes a firm's resources to be a potential source of competitive advantage, which may improve overall performance (Wernerfelt, 1984). Wernerfelt (1984) argued this means a firm has the ability to implement a value-creating strategy not simultaneously being implemented by current or potential competitors. The RBV is an influential theoretical framework for understanding how competitive advantage in firms is achieved and how advantage might be sustained over time (Barney, 1991, Peteraf, 1993, Wernerfelt, 1995). However, the usefulness of analyzing firms from the resource perspective was not popularized until the development of the RBV by Wernerfelt (1984).

The extant literature has examined the types of resources capable of providing competitive advantage to a firm. According to Barney (1991), there are three key RBV tenets. First, the firm's resources are heterogeneously distributed across firms, and any differences in these resources are stable. Second, there is an explicit link between a firm's resources, its management, and sustained competitive advantage. Last, there are four empirical indicators for firm resources to generate a sustained competitive advantage: valuable, rareness, inimitable, and non-substitutable—the so-called VRIN attributes.

The RBV theory focuses on how and why some resources and capabilities are valuable, yet rare, imperfectly imitable, and non-substitutable to allow firms to accrue economic returns (Barney, 1996). RBV scholars argued valuable and rare firm resources and capabilities can attain a short-term competitive advantage. They also contend these resources and capabilities must be inimitable and non-substitutable to produce a sustainable competitive advantage. However, each indicator could be considered necessary, but not enough to sustain a long-term competitive advantage.

Resources and capabilities are two terms often used without distinction. Barney (1991) classified resources into three categories: physical capital (e.g., financial assets and technology), human capital (e.g., managerial skills), and organizational capital (e.g., reputation, culture). Capabilities refer to a firm's capacity to deploy valued resources either in combination or in co-presence (Schendel, 1994). In addition, capabilities are also firm-specific and developed over time (Barney and Hansen, 1994). Competences like trustworthiness, organizational flexibility, rapid response to customer trends, and short product life cycles are considered capabilities. Based on the RBV theory definition by Wade and Hulland (2004), resources are inputs into a firm's production process (i.e. IT equipment), while capabilities is a firm's capacity to exploit IT equipment through organizational processes. Through continued use of IT equipment, capabilities become more difficult to understand and imitate by current or potential competitors. The literature shows a notable difference between resources and capabilities.

The RBV has been applied in IS literature to explain information systems (IS) and information technology (IT) business value, where a firm's resources determine its performance. For instance, a study by Caldeira and Ward (2003) applied RBV theory to identify and understand factors determining the successful adoption and use of IS/IT in (12) manufacturing SMEs. They argued several studies explored the applicability of RBV theory to IS/IT, mainly at a conceptual level.

Recent studies applied RBV theory as a frame of reference to understand how much different IS/IT capabilities contribute to business value. For instance, Ruivo et al. (2015) investigated factors contributing to enterprise resource planning (ERP) value creation in SMEs. Grounded on the RBV theory, they assessed a research model linking three identified determinants: ERP use, collaboration, and analytics. These explain ERP value in three effects: individual productivity, management control, and customer satisfaction. Similarly, a study by Uwizeyemungu and Raymond (2012) explored the potential link between ERP capabilities and their contribution to organizational performance. This contribution was conceptualized and measured through value added by automational, informational, and transformational effects of ERP capabilities on the firm's operational and managerial processes.

Similar studies have also looked at ERP from the resource-based perspective. For instance, a study by Laframboise and Reyes (2005) applied RBV theory to prove ERP implementation influences competitive position and performance only indirectly through interactions with other resources. Another study by Lengnick-Hall et al. (2004) examined ERP through the firm's RBV theory. Their results proved even if ERP is necessary to coordinate complicated, multifaceted operations, it is not enough to promote a strong, competitive long-term position. The authors argued people must change the culture to their work, the relationship they develop within and across firm boundaries.

Viewed from the resource-based perspective, knowledge management (KM) researchers have identified different KM related resources serving as potential sources of competitive advantage. Chuang (2004) employed the resource-based perspective to develop theoretical links and empirically examine the association between KM capability and competitive advantage. Since RBV theory explicitly recognizes the importance of KM resources and capabilities, it offers a significant opportunity to explore these theoretical complementarities in examining their relationship. Similarly, Gold et al. (2001) examined the issue of effective KM from the organizational capabilities perspective. They also noted that technological resources, structural resources, and cultural resources are rare and firm-specific. Therefore, these resources will likely serve as a source of organizational capability.

Using RBV theory as a theoretical base, a study by Chae et al. (2014a) expanded the understanding of the components and performance of supply chain analytics (SCA). They developed a theoretical perspective on SCA as a valuable, inimitable, and non-substitutable resource in manufacturing contexts as a source of sustained competitive advantage. SCA is a combination of three data sets and IT-enabled supply chain management (SCM) resources, referred to as data management resources, IT-based supply chain planning resources, and performance management resources. These three sets of resources are complementary, enabling each other. The authors acknowledged these resources in RBV theory are important to competitive advantage.

The firm's RBV is among the few theoretical perspectives informing BI&A research explicitly including firm performance as a dependent variable (Elbashir et al., 2008). A recent study by Olszak (2016) investigated BI&A issues using RBV as one of three theories. Her goal was to provide a theoretical and empirical discussion on comprehensive BI&A development. To do this, she distinguished four specific tasks to obtain the study's goal: (1) conceptualization of the BI&A issue, (2) identification of BI&A usage in a firm, (3) assessment of BI&A maturity in a firm, and (4) investigation of factors allowing a firm to achieve BI&A success and better business results.

The work of Chae et al. (2014b) examined the impact of two BI&A resources—accurate manufacturing data and advanced analytics—on firms' operational performance. Their study adapted RBV, suggesting the impact of primary resources on organizational performance is contingent on complementary resources. Similarly, Yogev et al. (2012) examined the business value associated with BI&A systems. Yogev and colleagues developed and tested an RBV-based research model to explain the unique mechanisms BI&A uses to create business value. They identified key resources and capabilities determining BI&A's impact on business processes and organizational performance. Fink et al. (2017) conducted a further study on BI&A value creation. They developed and tested a model of BI&A value creation. The analysis was drawn on the firm's RBV theory to hypothesize which BI&A assets and capabilities create business value.

2.2 The Dynamic Capabilities View

The theory of dynamic capabilities is an extension of the firm's RBV (Teece et al., 1997). The rationale is RBV does not sufficiently explain how and why certain firms can gain a competitive advantage in situations of rapid and unpredictable change (Eisenhardt and Martin, 2000). Teece and colleagues defined dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environment (p. 516)." They used the term 'dynamic' as the capacity to renew competences to achieve congruence in changing business environments. The term 'capabilities' was also used to emphasize strategic management's role in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences to address a changing environment's requirements. Teece et al. (1997) conjectured the more rapid the technological change, the more dynamic capabilities are the source of sustained competitive advantage.

According to Wernerfelt (1984), the firm's RBV invites using managerial practices to create new capabilities. This means current firm resources and capabilities are matched to marketplace opportunities. Dynamic capabilities suggest using management strategies to renew competencies according to environmental changes. This also means firms must develop a dynamic capabilities view to identify new opportunities and respond quickly to them (Teece et al., 1997). The dynamic capabilities view urges scholars to focus on how firms develop and renew their capabilities to respond to rapidly evolving environmental changes.

In IS literature, further studies were conducted to delineate the components of dynamic capabilities. For instance, Teece et al. (1997) attempted to propose a measurable model of dynamic capabilities by conceptualizing, operationalizing, and measuring dynamic capabilities. Teece and colleagues identified the following sets of capabilities: sensing, learning, coordinating, and integrating the environment. After a decade, Teece (2007) conducted another study and argued dynamic capabilities can be decomposed into organizational capabilities to sense environmental stimuli, determine an appropriate course of action, and transform the organization. The ability to sense new opportunities and threats is the first critical component of dynamic capabilities. Sensing is necessary, but it is not enough. Threats and identified opportunities must be seized by building consensus among stakeholders, making effective decisions, and investing organizational resources. Lastly, transforming the third critical component involves executing organizational decisions and plans based on threats and opportunities. This sense-seize-transform conceptualization of dynamic capabilities provides a detailed view of how organizational adaptation occurs and how it results in improved organizational performance. A study by Pavlou and El Sawy (2011) also distinguished between sensing, learning, integrating, and coordinating capabilities.

Another established framework consists of eight distinct dynamic IS capabilities, divided into three broad classes: inside-out, outside-in, and spanning (Wade and Hulland, 2004, Day, 1994). Inside-out capabilities tend to be internally focused and deployed to respond to market requirements and opportunities. Outside-in capabilities are externally oriented and focused on managing external relationships like anticipating market requirements, ensuring strong customer relationships, and understanding competitors. Finally, spanning capabilities involve both internal and external analysis and integrate the firm's inside-out and outside-in capabilities, like managing IS business partnerships, management, and planning.

Research on dynamic capabilities is an emerging field. Dynamic capabilities have been proposed to deal with rapidly changing environments and consider the evolving nature of a firm's resources and capabilities to adapt to change (Teece et al., 1997). For example, the work of Bernroider et al. (2014) explicated the project process potentially underlying the positive association between three selected dynamic capabilities and ERP enabled business capabilities. The three selected dynamic capabilities include external information acquisition, IT governance capabilities, and decision-making. The results showed the capacity for external information acquisition project and IT governance mechanisms influenced ERP business capabilities indirectly by the ERP implementation project. Thus, the authors suggested the effects of two out of three selected dynamic capabilities depend on the properties of the underlying organizational transformation project. This study also proved the dynamic capabilities are essential for ERP value creation in large organizations.

Similarly, Ma and Loeh (2007) adopted the dynamic capabilities approach to study ERP-driven process innovation programmes with various implementation outcomes. Their results showed the dynamic capabilities approach can offer a holistic perspective to understand enterprise system-driven process innovation at Chinese companies which face a dynamic external environment. The authors concluded even though these companies typically lack the experience of enterprise ERP-driven process innovation, focusing more on effectively building their dynamic capabilities could solve these challenges. A recent study was considered one of the first to explain how an enterprise can implement an ERP based on dynamic capabilities' theory (Chang et al., 2015a). A proposed ERP implementation model can serve as a guideline for enterprises interested in implementing ERP.

Also drawing on dynamic capabilities view, the work of Villar et al. (2014) has provided empirical evidence on KM practices' role in SME export intensity. Their results highlight the relevance of knowledge practices to foster exports, providing new insights for managers dealing with dynamic capabilities in SMEs. A study by Cepeda and Vera (2007) examined KM's influence to create and develop dynamic capabilities at a large Asia-based call center. A study by Landroguez et al. (2011) proposed a way to increase customer value. Their study identified possible combinations of the three organizational capabilities: market orientation, knowledge management, and customer relationship management. To analyze the potential interaction between these three, would lead to better customer value creation. Through dynamic capabilities, the authors explained the connection between the interaction of these three capabilities and superior customer value.

In the BI&A context, a recent study by Cao et al. (2019) applied dynamic capabilities view to posit a firm can sustain a competitive advantage from its sensing, seizing, and reconfiguring capabilities, manifested by BI&A usage. A research model was developed to explain how BI&A usage is linked to marketing decision-making, product development management, and sustained competitive advantage. Another recent study by Božič and Dimovski (2019b) examined the relationship between BI&A usage, innovation ambidexterity, and firm performance by relying on the process theory of IS value creation and the dynamic capabilities' perspective. Their results supported the notion that BI&A use is positively associated with successfully balancing explorative and exploitative innovation activities, which enhances firm performance. Similarly, Torres et al. (2018) also applied dynamic capabilities as the theoretical lens for examining BI&A's role in organizations. It viewed BI&A as the sensing and seizing components of dynamic capabilities to improve firm performance by enabling business process change. They also confirmed a positive relationship between BI&A and performance, mediated by business process change capabilities.

The work of Chae and Olson (2013) proposed a framework to understand how BI&A can support organizations. Drawing on the dynamic capabilities' perspective, they extensively described a set of three analytical capabilities needing proper attention: data management capability, analytical supply chain process capability, and supply chain performance management capability. In another study by Olszak (2014) applied both RBV and dynamic capabilities to investigate BI&A failures. She proposed a comprehensive, dynamic capabilities framework reflecting six BI&A capabilities areas: governance, culture, technology, people, processes, and change management and creativity. BI&A literature often fails to bridge the gap between normative specifications on BI&A use and competitive advantage. Therefore, Sidorova and Torres (2014) proposed BI&A as a mechanism for capability monitoring through the perspective of dynamic capabilities. The authors outlined five core internal components of BI&A: (1) collection and management of capability practices data, (2) collection and management of environmental data, (3) analysis of environmental data and identification of environment discontinuities, (4) identification of capability maladjustments, and (5) producing a request. They argued the study's results highlighted the theoretical link between BI&A and competitive advantage.

A recent study by Shamim et al. (2018) provided an important contribution to value creation knowledge from big data in emerging economies in the digitalized world. The authors emphasized the big data decision-making capability as dynamic capabilities and reflected the implications of managerial practices in developing dynamic capabilities in big data-driven environments. They proposed such capabilities are influenced by big data management challenges, like leadership, talent management, technology, and organizational culture. Grover et al. (2018) framed an understanding of how value is created from big data analytics using dynamic capabilities, indicating in turbulent environments, companies engage in capability building and realization by building, and configuring internal and external resources to improve organizational performance. Wamba et al. (2017) examined the direct effects of big data analytics on firm performance. The results confirmed dynamic capabilities' role in improving insights and enhancing firm performance.

2.3 IS Value Models

The business value of investments in IS/IT has been and is predicted to remain a major research topic for IS researchers (Schryen, 2013). The fundamental question of the causal relationship between IS investments and business value remains only partly explained. IS scholars adopted a myriad of approaches to know how firm investments generate business value. These eminent scholars are motivated by a desire to understand how the application of IT in firms leads to improved organizational performance (Melville et al., 2004). A precise specification of what we mean by IT business value is dependent on what we meant by IT. There are five conceptualizations of the IT artifact adopted in IS research: tool view, proxy view, ensemble view, computational view, and nominal view (Orlikowski and Iacono, 2001).

First, IT is viewed as an engineered tool to do what its designers intended (i.e. productivity enhancement and reshaping social relations). Second in the proxy view, IT is conceptualized by its essential characteristics defined by an individual perception of its usefulness or value, the diffusion of a system in a specific context, and its investment or capital stock denominated in financial units. Third the ensemble view, which focuses on interactions of people and technology in both IT development and use. Fourth, the computational view emphasized algorithm, systems development, testing, data modelling, and simulation. Last, the nominal view invokes technology in name, but not fact. For example, deriving a two-stage game analyzing the impact of IT application on total factor productivity in oligopolistic competition. IT was introduced solely via its posited impact on cost reduction and production differentiation (Belleflamme, 2001).

Researchers have proposed many theoretical models tracing the innovation path from the adoption decision through investment and resource creation to the desired outputs, such as increased productivity, improved organizational performance, and realized business value. For instance, Soh and Markus (1995) presented a process model of how, when, and why IT investment is converted to favorable organizational performance. They argued this proposed process model has captured all the major ingredients of the recipe for transforming IT investment into organizational performance. The recipe comprises necessary conditions and probabilistic processes in the following sequence: firms spend on IT and, subject to the varying degrees of effectiveness in IT management, obtain IT assets. The quality IT assets, if combined with the process of appropriate IT use, then yield favorable IT impacts. Favorable IT impacts, if not adversely affected during the competitive process, lead to improved organizational performance (Figure 2.1).

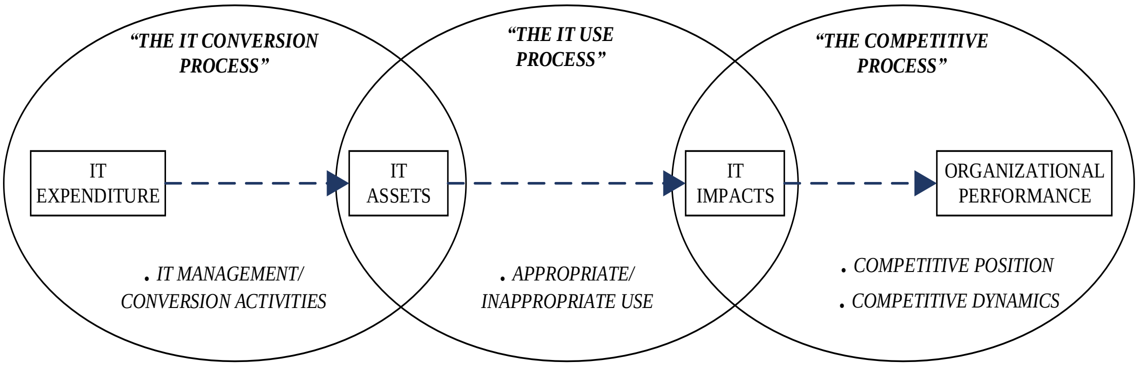

Figure 2.1: How IT creates business value: A process theory (Soh and Markus, 1995)

The limitation of conventional RBV theory according to Melville et al. (2004) is it assumes resources are always applied in their best uses, without explaining fully how this is done. Melville and colleagues have developed an IT business value model to provide an understanding of how IT resources are applied in business processes to improve organizational performance (Figure 2.2). This model of IS/IT business value was based on the firm's RBV integrating various strands of research into a single framework. The integrated model was built on accumulated modeling knowledge to disaggregate the focus of IS/IT business value into three domains: focal firm, competitive environment, and macro environment.

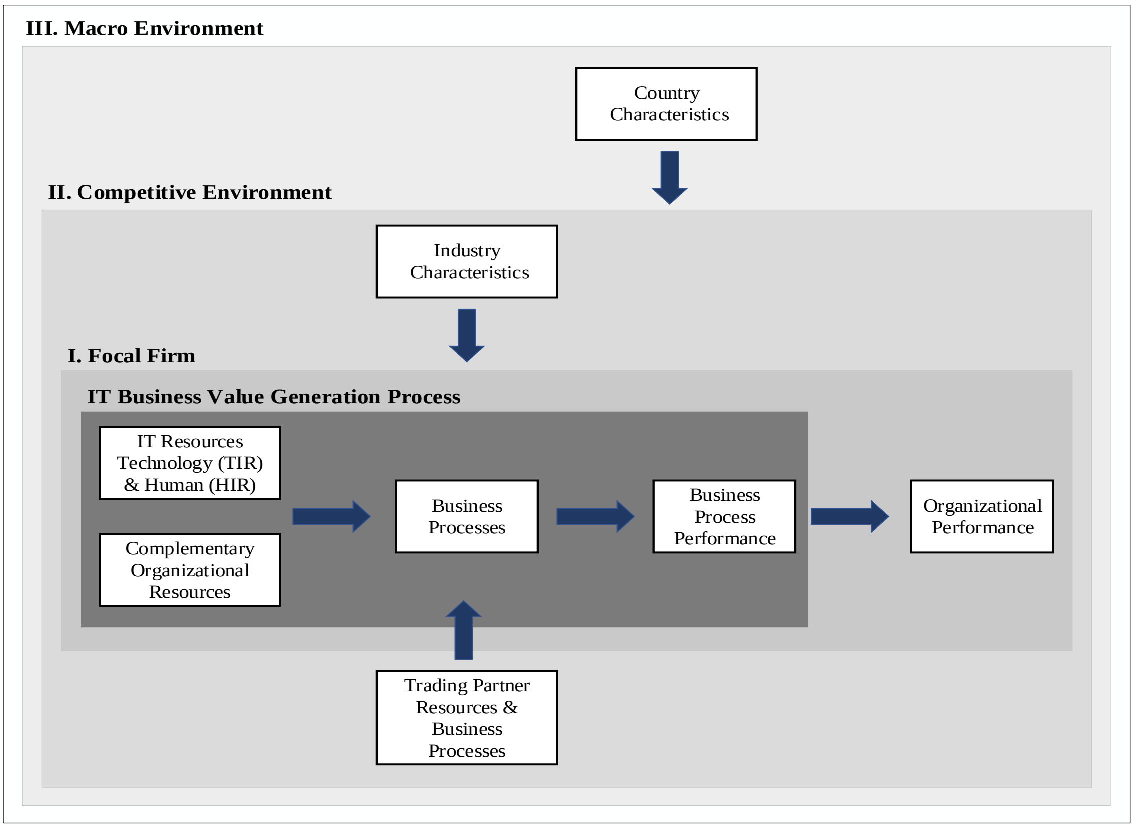

Figure 2.2: IT business value model (Melville et al., 2004)

To reactivate the researchers' interest and activities in IS/IT business value, Schryen (2013) provided a fresh perspective on how IS investments create business value. To answer this question and strengthen the role of IS value research, Schryen (2013) performed three research tasks: (1) Synthesize knowledge (what do we know?), (2) Identify the lack of knowledge (what do we need to know?), and (3) Proposition of paths to close the knowledge gap (how can we get there?). He defined and applied a new conceptual model based on four prominent IS business models proposed by Dedrick et al. (2003), Dehning and Richardson (2002), Melville et al. (2004), and Soh and Markus (1995). The synthesized IS business value model is shown in Figure 2.3.

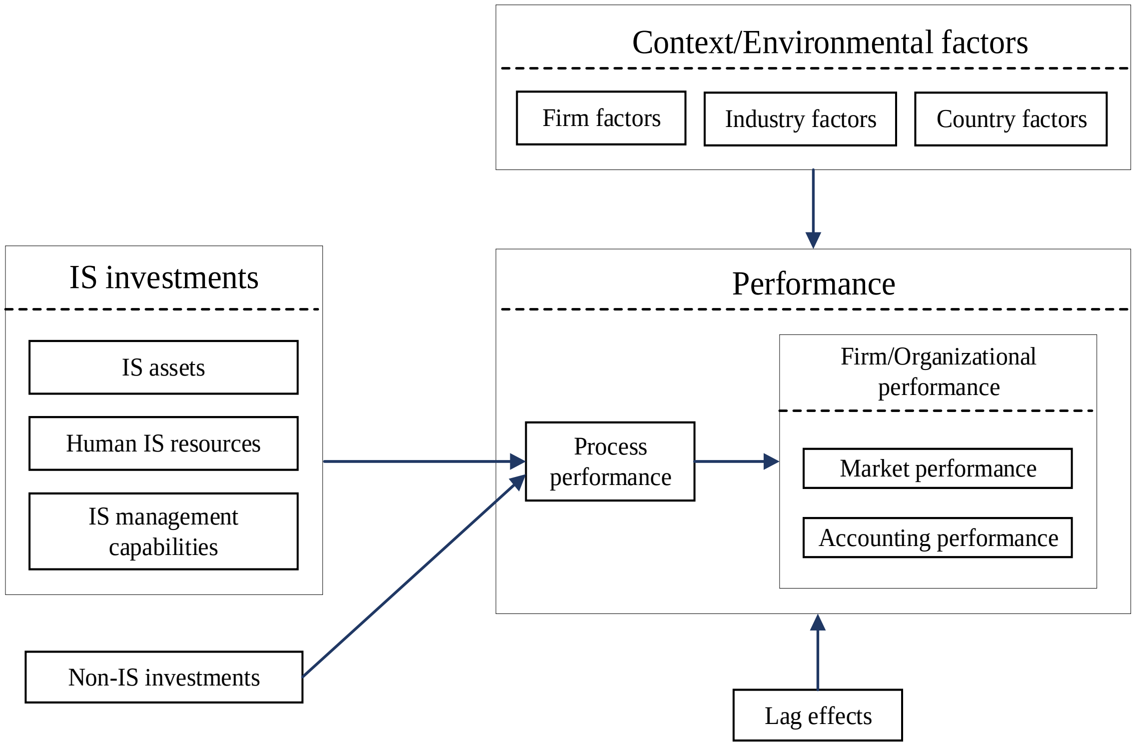

Figure 2.3: Synthesized IS business value model (Schryen, 2013)

Process theory recognizes variables change over time and interact with each other. This approach is particularly useful to study the conversion of IT investments into IT assets or the conversion of IT assets into organizational value. As mentioned above, Soh and Markus's framework describes the IT investment to the business value process as a series of three linked process models, namely, the IT conversion process, IT use process, and competitive process. Drawn from Soh and Markus's framework of IT value models, Raeth et al. (2010) examined what characterized the objectives, challenges, and actions involved in the organizational adoption of

Web 2.0 systems. They studied three organizations that successfully adopted the Web 2.0 system. Their results indicated the adoption of these systems differs from larger enterprise system adoption projects. This is rooted in lower implementation and maintenance costs and the lower technical complexity of Web 2.0 systems. Grounded in RBV and process theory by Soh and Markus (1995) and Melville et al. (2004), a conceptual model was composed to examine the casual structure of capability, process, and relationship in IT outsourcing (Han et al., 2008). The authors investigated firm's resource capabilities and interaction process effects on IT outsourcing success. The proposed model provided a paradigm to understand outsourcing relationships and how to nurture and ensure success.

A study by Scheepers and Scheepers (2008) developed a decision model to explore the business value potential of IT at the single business process level. The premise of the model is that, for a focal business process, decision-makers should consider the initial, intermediate, and long-term benefits from IT use ultimately contributing to organizational performance. These use stages were drawn on the "IT use process" of Soh and Markus (1995). They argued the proposed model can support managers in analyzing the overall business value returns from IT investments. Kumar et al. (2002) explored ERP adoption using the framework by Soh and Markus (1995). The framework models an organization's experience with ERP systems from adoption to success characterized by key players, typical activities, characteristics problems, appropriate performance metrics, and a range of possible outcomes. The authors focused on exploring the framework's adoption phase. The results yield several critical concerns in ERP adoption's organizational innovation process.

A recent study by Trieu (2017) reviewed and synthesized empirical 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&A. Adapting the IS/IT value models of Soh and Markus (1995), while incorporating constructs suggested by Melville et al. (2004), and Schryen (2013), Trieu (2017) presented a framework of how BI&A creates business value (Figure 2.4).

The basic idea of this framework is that the link from BI investments to organizational performance can be modelled as a chain of necessary conditions. For instance, increases in organizational performance require a necessary degree of BI impacts, which in turn require BI assets and investments. Following the logic of process models of Soh and Markus (1995), each link in the chain reflects a probabilistic process. For instance, the link from BI investments to BI assets involves the process of BI management/conversion and investment in complementary non-BI investments. Then, the link from BI assets to BI impacts depend on the process of using BI systems effectively. However, the link from BI impacts to organizational performance depends on the competitive process. The findings of her study showed organizations appear to obtain value from BI&A according to the process suggested by Soh and Markus (1995). Further, her study identified several opportunities to provide a more complete picture of how organizations can obtain value from BI&A.

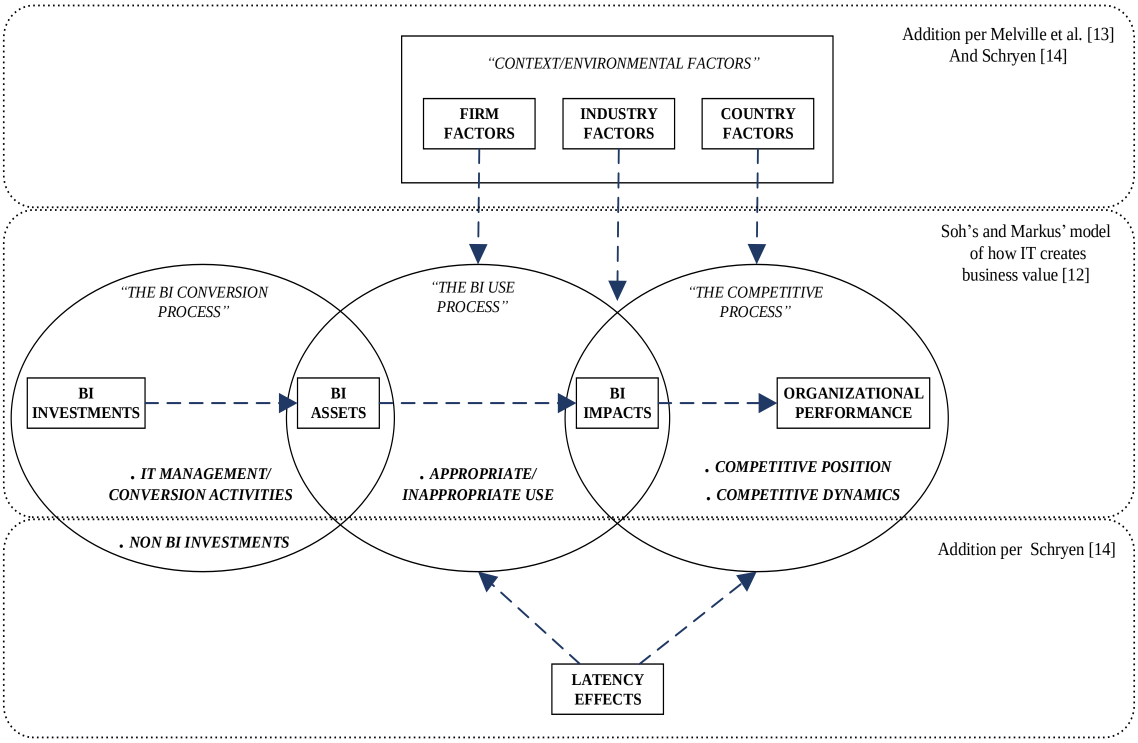

Figure 2.4: A framework of how BI&A creates business value (Trieu, 2017)

Another study attempted to understand how an organization can realize business value from BI&A investment (Smith and Crossland, 2008). An extended IS business value process model based on Soh and Markus's was used as a framework. The results of the study proved the realization of BI&A business value was highly dependent on activities occurring in all stages of the IS value process model. Similarly, Eybers et al. (2013) also applied a customized model based on the process model of Soh and Markus (1995) to investigate the business value of BI&A. The findings are that business value is realized on various activities across all the processes on Soh and Markus's framework. The authors argued business value is challenging to measure due to the indirect and delayed onset of benefits.

Together with dynamic capabilities, Grover et al. (2018) also applied the IS value models proposed by Soh and Markus (1995) and Melville et al. (2004) to describe how IT investments build assets or resources and create impacts on both process and variance representation in big data analytics. They proposed a conceptual framework to create value from big data analytics based on these theories.

3 Related Literature

This chapter provides an overview of literature related to the thesis' research topics. I start by introducing a brief discussion of decision support technologies (3.1), followed by defining the context of BI&A in IS literature (3.1.1). I also examine literature on BI&A architecture (3.1.2), BI&A evolution and trends (3.1.3), and BI&A value creation (3.1.4). In Chapter 3.2.1, I introduce the SME context and environment in the IS domain. This chapter will define the scope of the research context, which may impact BI&A adoption. The unique characteristics of SMEs are presented in Chapter 3.2.2. I also examine the literature on adopting IS generally (3.3) and in SMEs (3.4). I briefly discuss adoption theories and factors influencing IS adoption found in the literature. Chapter 3.5 discusses current literature on adoption theories and factors influencing BI&A adoption. Finally, a brief discussion of BI&A adoption literature in SMEs is presented (3.6). This review is not comprehensive, but rather complements the relevant topics discussed in this thesis.

3.1 Business Intelligence and Analytics

From the information systems (IS) research perspective, BI&A provides the latest technological foundation for data collection, integration, and analysis of unprecedented volumes and types of data to improve available information quality in decision-making (Chen et al., 2012, Wixom and Watson, 2010, Chaudhuri et al., 2011).

In the 1960s, organizations began developing IS to computerize many business operations (Arnott and Pervan, 2005), such as order processing, billing, inventory control, payroll, and accounts payable. The evolution starts by introducing the first data processing systems. The Management Information Systems (MISs) were developed to make information in transaction processing systems available to management for decision-making. After some decades, these systems evolved through several stages. Personal Decision Support Systems (PDSSs) are the oldest form of Decision Support System (DSS), effectively replacing MIS as the management support approach choice. PDSSs are small-scale systems normally developed for a few independent managers. The evolution continued to Executive Information Systems (EISs), which are data-oriented DSSs that provides reporting of an organization's nature to management. The need for continuous high-quality data about the organization's operations was created by developing large-scale EISs.

In the 1990s, large organizations faced significant challenges in maintaining their business's integrated view, so Data Warehouses (DWs) were developed. A DW is a set of databases created to provide information for decision-makers (Cooper et al., 2000). DWs also provide raw data for user-focused decision support through PDSS and EIS (Arnott and Pervan, 2005). Data processing capabilities increased at each stage of evolution, from DWs to current state-of-the-art BI&A. This improved the available data basis or analytic capabilities to offer advanced data analysis capacities (Arnott and Pervan, 2005, Arnott and Pervan, 2008, Arnott and Pervan, 2014). Business Intelligence (BI) and Business Analytics (BA) represent two recent decision support technology after DWs. Figure 3.1 was based on Arnott and Pervan (2014), Humm and Wietek (2005), and Shollo and Galliers (2016).

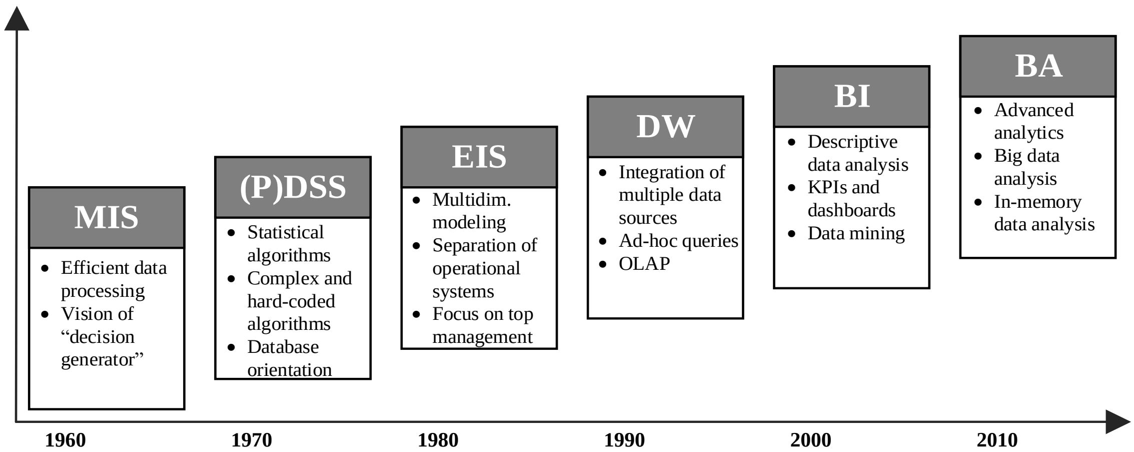

Figure 3.1: Evolution of decision support technologies

3.1.1 Business Intelligence, Business Analytics, and Big Data

As mentioned above, the two recent stages in the evolution of decision support technologies are Business Intelligence (BI) and Business Analytics (BA). BI is an overarching term for decision support systems based on data integration and analysis to improve business decision-making (Fink et al., 2017). The term BI was first coined by Hans Peter Luhn in 1958 (Yeoh, 2008), but Howard Dresner of the Gartner Group re-introduced the term in 1989 (Burstein and Holsapple, 2008), describing it as a broad category of software and solutions for gathering, consolidating and analyzing, and providing access to data in a way that let enterprise users make better business decision (Gibson et al., 2004). However, the

BI label did not gain widespread traction as a DSS movement until the early 2000s (Arnott and Pervan, 2014).

In the late 2000s, BA rose to prominence in analysis (Arnott and Pervan, 2014). BA was defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and action (Davenport and Harris, 2017, p. 7)." There was a debate about BI's and BA's definition similarities (Arnott and Pervan, 2014). Despite the wide use of both terms by software vendors and consultants, most practitioners failed to see a significant difference between the two terms. The term BA also represented the key analytical component in BI (Chen et al., 2012). Thus, the term business intelligence and analytics (BI&A) is proposed (Chen et al., 2012) to describe information-intensive concepts and methods to improve business decision-making (Chiang et al., 2012). This thesis adopts Chen et al.'s (2012) unified BI&A concept.

BI&A is integral to twenty-first century business due to increasing needs in analysis, interpretation, and data processing. Over time, the definition for BI&A has broadened to include both technology and organizational and business processes (Brooks et al., 2015). BI&A's main objective is to improve the timeliness and quality of information available for decision-making. Actionable information must be delivered correctly to the right place at the right time (Negash, 2004).

BI&A is an important area of academic research, with big data analytics being a related field (Chen et al., 2012). Big data is often used to describe massive, complex, and real-time streaming data requiring analytical and processing techniques to extract insights. The term initially reflected the voluminous size of data generated from new technologies like social media, smart phones, and sensors (Kowalczyk and Buxmann, 2014). The established definition of big data was based on the 3-V model (Klein et al., 2013). The 3-V model comprises three dimensions of challenges in data growth: volume, velocity, and variety. Volume is the amount of data. Velocity describes the speed of new data creation and how quickly data can be accessed for analysis. Variety depicts the range of data sources and types. A fourth V, value, was proposed, stressing the importance of doing something valuable with the data (Lycett, 2013). Significant research focuses on technical issues associated with managing big data and surrounding BI&A initiative implementation (Sidorova and Torres, 2014). Big data's opportunities and challenges continue to motivate BI&A research.

3.1.2 BI&A Architecture

Several existing BI&A architectures can be found in literature (Baars and Kemper, 2008, Shariat and Hightower Jr, 2007, Turban et al., 2008, Watson, 2009). These architectures differ in structures (e.g., layers, components, processes, and relationships) guiding BI&A implementation efforts (Shariat and Hightower Jr, 2007). However, some common components among these BI&A architectures include source systems, data storage, and reporting tools. Other scholars proposed including another important component missing from these BI&A architectures: analytical and reporting components (e.g., data mining, predictive analytics, and data visualization) (Ong et al., 2011, Khan and Quadri, 2012, Chaudhuri et al., 2011). They argued these features are important BI&A capabilities that should be included in BI&A architecture.

A typical BI&A architecture includes a data source layer, an Extract-Transform-Load (ETL) layer (the staging area), a data warehouse (DW) layer, an end user layer, and a metadata layer (Ong et al., 2011). The data source layer may contain both internal and external data sources. Internal data sources are data captured and maintained in an organization, for example, customer relationship management (CRM) and ERP. External data sources refer to data originating outside an organization, like the internet and market search. The ETL layer or staging area focuses on three main processes: extraction, transformation, and loading (Baars and Kemper, 2008). Extraction is the process of identifying and collecting relevant data from different sources (Reinschmidt and Francoise, 2000). Extracted data is then sent to temporary storage called the staging area prior to the transformation process (Ranjan, 2009). Transformation is the process of converting data based on the set of business rules into consistent formats for reporting and analysis (Ong et al., 2011). Loading is the last process where staging area data is loaded into the target repository.

The DW layer is very important to these five layers. It is a central storage collecting and storing data from internal and external sources for decision-making, queries, and analysis (Bara et al., 2009). This layer also involves storing aggregated data, summarized data, and much historical data for long-term analysis. The metadata layers refer to data about data. This layer describes where the data is being stored and what changes have been made to the data. The metadata repository is also used to store both technical and business information about data, business rules, and data definitions (Davenport and Harris, 2007). The end user layer consists of tools displaying information in various formats to various users. These tools include query and reporting tools, OLAP, data mining, data visualization, and analytical applications (Ong et al., 2011). The typical BI&A architecture is shown in Figure 3.2.

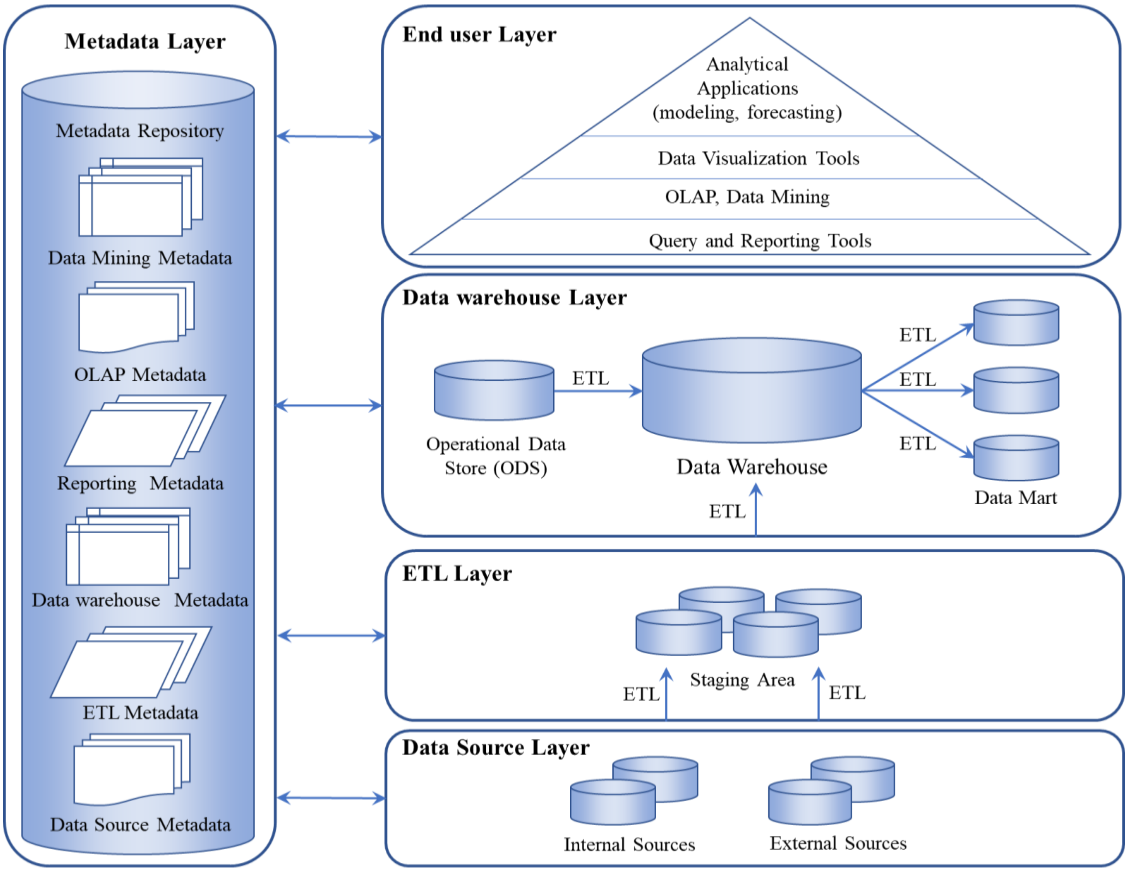

Figure 3.2: BI&A architecture (Ong et al., 2011)

3.1.3 BI&A Evolution and Trends

BI&A systems allow decision-makers to query, understand, and analyze business data to improve decision-making and gain competitive advantages. BI&A applications leverage large data infrastructure investments (e.g., ERP, CRM) made by business, and could realize the substantial value locked up in an organization's data resources (Elbashir et al., 2008).

A data-centric approach to BI&A has its roots in the long-standing database management field (Chen et al., 2012). BI&A relies heavily on numerous data collection, extraction, and analysis technologies (Chaudhuri et al., 2011, Watson and Wixom, 2007). Traditional BI&A solutions, or BI&A 1.0 focus on analyzing historical data to provide business status through reports (Chen et al., 2012). A sales report may include rows and columns representing sale reps, orders taken, units sold, revenue generated, and percentage of target achieved. The data collected by organizations through legacy systems are mostly structured and often stored in commercial relational database management systems. The cornerstone of BI&A 1.0 is the technology allows organizations to access, analyze, and present information.

The Internet and the Web began to offer unique data collection, analytical research, and development opportunities in early 2000s (Chen et al., 2012). It is no longer enough to use only information from the organization itself and make isolated decisions. Therefore, traditional BI&A no longer limit analysis to data in their own organization. A new trend in BI&A systems emerged, allowing organizations to source their data from outside to provide richer business insights and better decision-making. The data generated from the web, like competitor retail prices or opinions posted by customers, are considered equally important. This information is a new gold mine for organizations to understand customer needs and identify new business opportunities. BI&A aims to provide a comprehensive view of the market and business environment. Thus, BI&A systems using only internal data no longer suffice.

Based on the web's evolution and other emerging technologies, BI&A started to include web data. BI&A are also evolving to BI&A 2.0 (Chen et al., 2012). The immense amount of data on company, industry, product, and customer on the web can be visualized through different text and web mining techniques. Web analytic tools, like Google Analytics, provide a trail of the user's online activities and reveal the user's browsing and purchasing patterns. Data mining is also a popular and indispensable tool to identify business opportunities in the sales and market of new products. BI&A, based on data mining, helped uncover hidden patterns in sales and markets (Cheung and Li, 2012). Unlike BI&A 1.0, already integrated into commercial enterprise IT systems, BI&A 2.0 will require integrating mature and scalable techniques in text mining, web mining, and social network analysis with existing DBMS-based BI&A 1.0 systems. This transformation was influenced by the apparition of different and new technologies in web 2.0 and the rise of social networks (Zorrilla et al., 2011).

BI&A has also been transformed into BI&A as a service, and data warehousing is now distributed in the cloud. Several studies discussed cloud BI&A and software-as-a-service (SaaS) BI&A. For instance, BI&A as a service, which is a cloud-based service, was designed to improve the accuracy and quality of both pricing and risk analysis in financial markets (Chang, 2014). In addition, cloud BI&A systems were developed for manufacturing, allowing different machines to work collaboratively and efficiently (Xu, 2012). The added values of cloud BI&A for business perspectives were also discussed in the literature (Marston et al., 2011). Cloud BI&A also provides several advantages to SMEs, like lower implementation costs and greater ease of use (Horakova and Skalska, 2013). Several studies proposed cloud BI&A frameworks for SMEs, like the conceptual framework for cloud-based open platform BI&A (Hiziroglu and Cebeci, 2013, Liyang et al., 2011), theoretical frameworks (Gash et al., 2011), and frameworks for consolidated Cloud BI&A (Muriithi and Kotzé, 2013). Prior research presented both the opportunities and risks of adopting cloud BI&A (Rostek et al., 2012).

Mobile devices and other sensor-based Internet-enabled devices equipped with radio-frequency identification, barcodes, and radio tags, the so-called “Internet of Things” (IoT), have opened new steams of innovative applications for BI&A. Most businesses rely on Internet and mobile technologies for daily operations (Airinei and Homocianu, 2010). The mobile industry has experienced tremendous growth and a new employee-driven IT revolution is taking place due to the emergence of powerful consumer technologies (Harris et al., 2012). The mobile and sensor-based content is the BI&A 3.0 (Chen et al., 2012). Mobile BI&A is an example of aligning IT strategies with enterprise strategies to gain a competitive advantage (Stipić and Bronzin, 2011).

There are few studies found in the literature on mobile BI&A. For instance, a single case study proposed and evaluated a mobile BI&A implementation framework to demonstrate its practical applicability (Verkooij and Spruit, 2013). An android-based mobile BI&A was proposed and identified the critical parameters of the production line in effectiveness measurement and machine utilization (Djatna and

Munichputranto, 2015). Some studies explored the concept of mobile BI&A in interpretation and legitimation (Tona and Carlsson, 2013) and highlighted the barriers to overcome and challenges to respond to (Airinei and Homocianu, 2010).

3.1.4 BI&A Business Value Creation

BI&A systems support and improve decision-making, which can lead to improved organizational performance. Deploying BI&A is a complex, time-consuming, and expensive voyage for most organizations. Improper BI&A implementation can lead to failure and render organizations data rich and information poor, making BI&A a risky IT investments requiring IT and business executive collaboration (Wagner and Weitzel, 2012, Ahmad et al., 2016).

Business value is predicted to remain a major research topics for IS researchers (Schryen, 2013). The most important research questions in IS involve measuring business value (Melville et al., 2004). Implementing BI&A alone cannot guarantee improved business outcomes. The true business value of BI&A systems hides in improved business processes and performance (Popovič et al., 2010). There are two conceptualizations of business value defined in the literature: strategic and operational business value (Yogev et al., 2012). Strategic value is value reflecting the creation of a competitive advantage by supporting strategic objectives, like identifying business opportunities and threats, efficiency improvement, running successful research and development, process optimization, financial performance improvement, and time and cost reduction (Davenport, 2006, Fink et al., 2017). Operational business value is value reflecting improvements in internal processes, like enhancing customer relations, saving cost and time, improving effectiveness, and market share (Watson and Wixom, 2007, Fink et al., 2017).

Although BI&A importance is widely accepted, how organizations obtain business value from BI&A has not been fully investigated (Elbashir et al., 2013, Moreno et al., 2018). BI&A appears to be a promising technology in recent value creation, at least in IT executive attitudes (Kappelman et al., 2013). Despite this dramatic shift, little empirical research has captured BI&A value creation processes (Moreno et al., 2018, Trieu, 2017, Fink et al., 2017, Božič and Dimovski, 2019a).

Recent literature highlighted the ability of organizations to create value through BI&A use (Chen et al., 2012, Larson and Chang, 2016, Wixom et al., 2013). Chen et al. (2012) explored BI&A's role in acquiring intelligence on customer needs, leading to new business opportunities. Wixom et al. (2013) explored two themes for maximizing BI&A business value: speed to insight and pervasive use. They also provided recommendations for how IT leaders can maximize value from BI&A investments. Many researchers recognize the interplay between BI&A and business value and provide ample evidence of these technologies' uses. Tamm et al. (2013) explored different types of BI&A use and argued BI&A tools and capabilities can only generate value if used. Their findings resulted in identifying two types of BI&A users: analytics professionals and analytics end users. This led to identifying three pathways to BI&A creation: provision of advisory services, creation and enhancement of BI&A tools and BI-platform, and use of BA tools by end users. Other studies explored using BI&A for improved business understanding before decision-making (Namvar and Cybulski, 2014) and captured the essence of BI&A for optimizing organizational performance (Mathrani and Mathrani, 2013). Ereth and Baars (2015) defined concrete BI&A application scenarios and analyzed them in business value and feasibility.

Some studies presented models or frameworks to explain the business value of BI&A. Seddon et al. (2017) presented a model of factors explaining how BI&A contributes to business value synthesized from the literature. A study by Popovič et al. (2010) proposed a conceptual model to assess BI&A business value developed on extensive literature review in-depth interviews and case analysis. Other models were presented and tested using data from larger enterprises (Moreno et al., 2018) and the semiconductor industry (Hou, 2016). A conceptual framework of value creation from BI&A use in competitive sports is also addressed in the literature (Caya and Bourdon, 2016).

A recent study by Božič and Dimovski (2019a) examined how BI&A triggered insights are transformed into valuable knowledge to offer a better understanding of BI&A value creation. They also identified the role of four absorptive capacity capabilities in insight generation and exploitation. These include acquisition, assimilation, transformation, and exploitation. Trieu (2017) conducted a literature review to investigate which part of BI&A's value process has been identified and are still most in need of research. Using several acknowledged frameworks from

IS literature utilizing a process theory approach (Melville et al., 2004, Schryen, 2013, Soh and Markus, 1995), Trieu's value framework analysis revealed five themes to motivate further research. These include context and environmental factors, BI&A conversion process, BI&A use process, BI&A competitive process, and latency effects. Fink et al. (2017) also identified several studies and developed a model of BI&A value creation. They examined the relationship between BI&A assets and capabilities, the distinction between strategic and operational business value, and the influence of learning and innovation as organizational resources. BI&A assets consist of BI&A technology (hardware and software), human resources (knowledge and skills), and application portfolios (Schryen, 2013, Trieu, 2017). BI&A capabilities are critical functionalities of BI&A to help the organization improve performance and adapt to change (Watson and Wixom, 2007). Fink and colleagues confirmed BI&A creates value from assets through capabilities to value at both operational and strategic levels. This path is moderated by specific organizational resources. None of these studies directly addressed BI&A value creation in SMEs.

3.2 Small and medium-Sized Enterprises and Information Systems

Over the last couple of decades, small and medium-sized enterprises (SMEs) have become more important both numerically and economically (Olszak and Ziemba, 2008). SMEs are the engine of the European economy, driving job creation and economic growth (IFC, 2012, p. 1). They outnumber large enterprises considerably, employ vast numbers of people, and help shape innovation. Therefore, the need to improve SMEs' worldwide competitiveness is crucial.

3.2.1 The SME Context and Environment

In IS literature, context has been defined by several researchers. Cappelli and Sherer (1991) defined context as "the surroundings associated with phenomena which help to illuminate that phenomena, typically factors associated with units of analysis above those expressly under investigation (p. 56)." Mowday and Sutton (1993) defined it as "stimuli and phenomena that surround and thus exist in the environment external to the individual, most often at a different level of analysis (p. 198)." The importance of context has been also highlighted in IS literature. Avgerou (2001) stated, "It could be argued that all information systems studies are contextual, as they address issues of technology implementation and use within organizations rather than in a laboratory setting. Thus, by the nature of the object of its study, information systems research considers a changing entity within its environment (p. 44)."

Firm size is an important variable explaining strategic behavior, performance, and an organization's competitive advantage (Raju et al., 2011, Fiegenbaum and Karnani, 1991). SMEs often do not have advantages as large enterprises in economies of scale, bargaining power with suppliers and distributors, brand name recognition, experience curve effects, and monopoly power to set prices above the competition (Fiegenbaum and Karnani, 1991). Traditionally, the SME environment was assumed to be local and artificially segregated from other markets, particularly the international competitive environment (Etemad, 2005). They are often intimated in some way, insulated from the threat of larger multinational enterprises (Darcy et al., 2014). The rise of the Internet has radically transformed many SMEs' competitive landscape. SMEs had to face the emergence of world markets and the need for quality, fast delivery, and partnerships, just as their larger counterparts (Levy et al., 2003).

Collaboration of SMEs with large enterprises is common. These alliances encourage innovating, sharing resources, forging new supplier relationships, and expanding product portfolios (Levy et al., 2003). These are important to SMEs who fail to participate globally alone. Most SMEs normally produce a few standard products for a narrow range of customers, making them critically dependent on these customers with little power to raise prices (Levy and Powell, 1998). SMEs are dependent on their customers in two instances. First, when the SMEs are just starting out. Second, when the SME is established as a first-tier or preferred supplier to a major customer (Levy et al., 2003). Therefore, market uncertainty is usually strong as SMEs usually have small market shares, few major customers, and relatively little power to influence prices (Levy et al., 2003).

The competitive environment of SMEs profoundly affects the owner-manager's perception of risk and business failure (Storey, 2016). Both the owner's age and experience are important factors in IS adoption decisions (Palvia and Palvia, 1999), making the owner-manager's role crucial. SMEs are also less responsive to competitor benchmarking, government agencies, and public or private interest groups (Dex and Scheibl, 2001). However, SMEs must move beyond traditional sources of competitive advantage and embrace the changes and dynamism of their internal and external environments to ensure this advantage and increase the likelihood of sustainability (Darcy et al., 2014). The demands for SMEs to identify and nurture sources of competitive advantage are also crucial to their long-term success and sustainability.

3.2.2 The SMEs' Unique Characteristics

SMEs exhibit very different characteristics than large enterprises affecting their information-seeking practices and the way they operate (Lang et al., 1997). According to the literature, flexibility is a main characteristic attributed to SMEs (Storey, 2016, Fiegenbaum and Karnani, 1991, Gupta and Cawthon, 1996). SMEs' survival is often ascribed to their adaptability and speed of response to environmental change (Levy and Powell, 1998). Therefore, SMEs are often more flexible than large enterprises. Other scholars believe flexible manufacturing provides a means of allowing SMEs to provide customers with new and innovative products from responding flexibly to market demands (Gupta and Cawthon, 1996). Organizational culture is also critical for an SME to be flexible, particularly in a culture inspiring learning over control.

SMEs also have the reputation of being able to respond readily to customers' changing needs (Levy and Powell, 1998). One reason is mainly because SMEs' owners have considerable knowledge of the firm's capabilities. SME is often understood in the psychological characteristics of the entrepreneur or owner-manager (Jenkins, 2004). These characteristics will vary widely, depending on individual personalities and differing ownership structures. The SME's management structure is normally flat with no bureaucracy. Since management teams are relatively small, most owner-managers work together on a day-to-day basis (Gupta and Cawthon, 1996), making SMEs intrinsically more innovative than large enterprises, especially in the industry lifecycle's early stages (Acs and Audretsch, 1987, Audretsch, 2002). It is not only because of SMEs being less bound by bureaucracy, but also because they are less bound by cumbersome organizational systems (Lefebvre and Lefebvre, 1992).

The limitations of an owner-manager in specialists or expertise was highlighted in the literature (Carson, 1985). The authors argued owner-managers tend to be more generalists than specialists. Thus, this shortcoming impedes the ability of owner-managers to recognize the importance of forward planning and strategic planning initiatives. Another characteristic of SMEs is the tendency to employ generalists rather than specialists (Mintzberg, 1989). Even if they wanted to recruit IT specialists, they face difficulties in attracting and retaining skilled IT staff because of the limited career paths available in a small business (Thong, 1999). Another study depicted how the SMEs' failure to plan the introduction and exploitation of new technology is due to management limitations (Levy et al., 2001). These limitations may include top management and management teams having little experience, skills, or interest in exploiting technology (Rothwell et al., 1989).

SMEs and large enterprises also differ in resources. Barney (1996) defined a firm's resources as financial, physical, human, and organizational assets used by the firm to develop and deliver products or services to the customer. Firm resources include a variety of elements, like assets, capabilities, and information. These resources are often the key to sustained competitive advantage and superior performance (Raju et al., 2011). Typically, SMEs do not have in-house technical skills (Igbaria et al., 1998, Blili and Raymond, 1993) and have limited financial resources (Levy and Powell, 2000, Gable and Stewart, 1999). Darcy et al. (2014) argued an early recruit to an SME must quickly add value and make meaningful contributions. Due to their limited resources, SMEs lack both the capacity to carry staff who do not make contributions and the slack resources to make them more vulnerable to environmental effects and misjudgments (d'Amboise and Muldowney, 1988).

The extensive training and development of employees in large enterprises may not be possible for an SME. This lack of formal training may be due to both the cost or market price of training, and the inappropriate content for an SME (Storey and Westhead, 1997). SMEs also lack a focused, deliberate, strategic approach for strategy formulation and implementation. The ability of owner-managers to recognize the importance of strategy formulation and implementation to the firm's performance is crucial (Darcy et al., 2014). Unlike large enterprises with necessary structures and people for planning and strategy formulation, SMEs suffer from resource gaps in a lack of staff, expertise, and time (Matthews and Scott, 1995). Therefore, sophisticated strategy formulation and implementation tools may not be available for SMEs. Burns (2016) depicts SMEs as social entities revolving around personal relationships, often suffering from limited financial resources, likely to operate in a single market, struggling to diversify business risk, and being more vulnerable to customer loss.

3.3 IS Adoption

IS adoption is an organization's decision to acquire a technology and make it available to users (Hu et al., 2000). IS adoption greatly affects business organizations and can lead to business procedure, organizational structure, and managerial power changes. Computer-mediated communication technologies like e-mail, the Web, interorganizational systems, and electronic data interchange have dramatically changed business processes (Premkumar, 2003). The IS/IT applications enabling information sharing across business processes and value chains can include ERP, CRM, and SCM (Al-Jabri and Roztocki, 2015). These and other applications collect, compile, and deliver information and establish business partner links.

Most studies in IS literature consider three stages of adoption, even with no consensus on their names: perception, adoption, and implementation (Ko et al., 2008); evaluation, adoption, and routinization (Junior et al., 2019, Hameed et al., 2012); evaluation, adoption, and use (Puklavec et al., 2018); initiation, adoption, and routinization (Ahmadi et al., 2017); adoption, assimilation, and implementation (Wu and Chen, 2014), or pre-adoption, adoption-decision, and post-adoption (Hameed et al., 2012). Cruz-Jesus et al. (2019) defined the three stages of adoption. The first stage relates to initial awareness and innovation assessment. The second stage consists of the adoption process after the decision to adopt has been made. The last stage pertains to routinization or maturing of the technology in the organization.

IS being used to achieve a competitive advantage has always been a focal issue (Johnston and Vitale, 1988, Rackoff et al., 1985). Many organizations began adopting IS strategically to reap a significant competitive advantage. IS literature provides a wide body of research explaining the adoption and use of IS/IT. This results in various theories, models, frameworks, success factors, antecedents, and determinants widely used to gauge IS adoption.

There are numerous theories on technology adoption in IS literature. The most used theories are the technology acceptance model (TAM), the theory of planned behavior, the unified theory of acceptance and use of technology (UTAUT), the diffusion of innovation theory (DOI), and the technology, organization, and environment (TOE) framework. The two prominent adoption models at the firm level in IS literature are the DOI and TOE framework (Oliveira and Martins, 2011). DOI is a theory of how, why, and at what rate new ideas and technology spread through cultures at the individual and firm level (Rogers, 1995). It sees innovations as being communicated through certain channels over time and within a particular social system (Oliveira and Martins, 2011). Thus, it provides a thorough analysis of innovation diffusion drivers and constraints, along with insights into the process of adopting and not adopting an innovation (Cruz-Jesus et al., 2018). The innovativeness of the DOI theory at the firm level is related to independent variables like individual characteristics, internal organizational structural characteristics, and external characteristics (Rogers, 1995). This is further described in Figure 3.3.

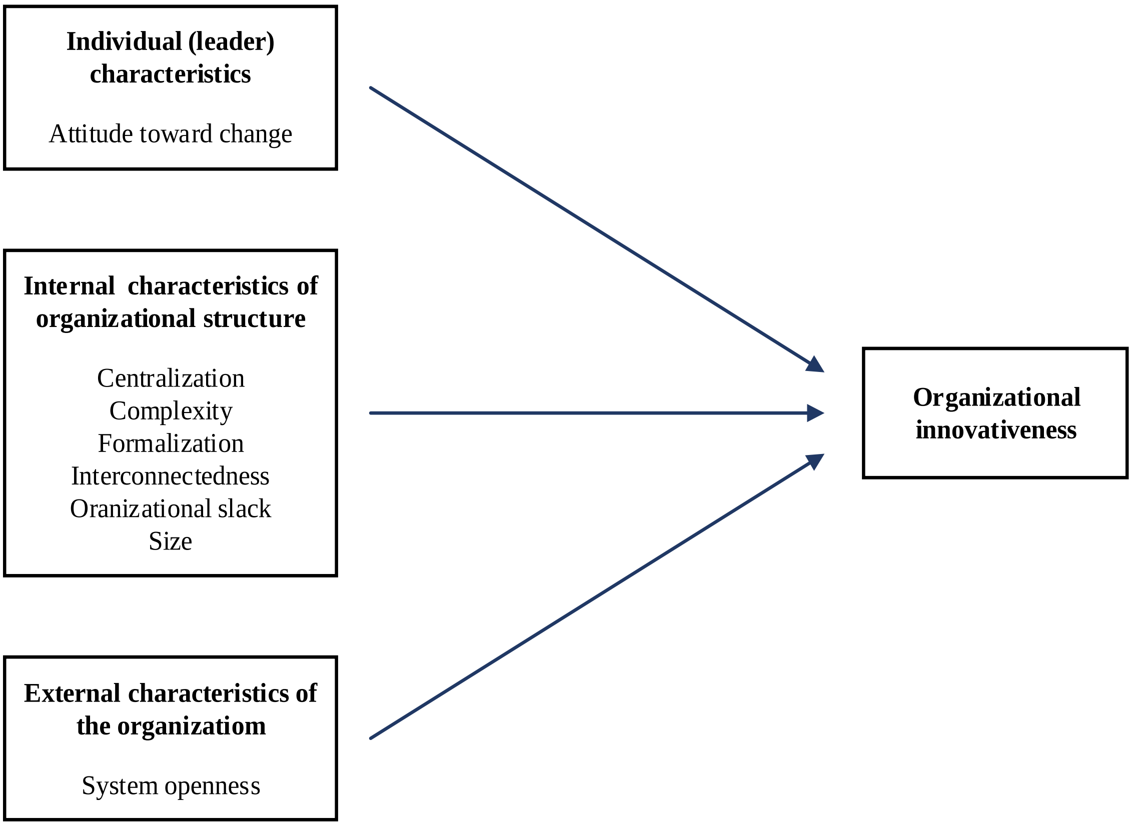

Figure 3.3: The diffusion of innovations framework (Rogers, 1995)

Since the early applications of DOI to IS research, the theory has been applied in various ways: intranet (Eder and Igbaria, 2001), website (Beatty et al., 2001), e-business (Zhu et al., 2006), ERP (Bradford and Florin, 2003), and CRM (Ko et al., 2008). A study by Mustonen-Ollila and Lyytinen (2003) showed that several factors recognized in DOI theory influence IS adoption. These factors include user need recognition, technological infrastructure, past technological experience, own trials, autonomous work, ease of use, learning by doing, and standards.

The TOE framework comprises three elements of a firm's context influencing the adoption process: technological, organizational, and environmental contexts ((Tornatzky et al., 1990); Figure 3.4). First, the technological context describes the firm's relevant internal and external technologies: their current internal practices and equipment (Starbuck, 1976) and the set of available external technologies (Thompson, 1967). Second, the organizational context refers to organizations' descriptive measures, like size, scope, and managerial structure. Finally, the environmental context where organization conducts business—its industry, competitors, and dealings with the government (Tornatzky et al., 1990).

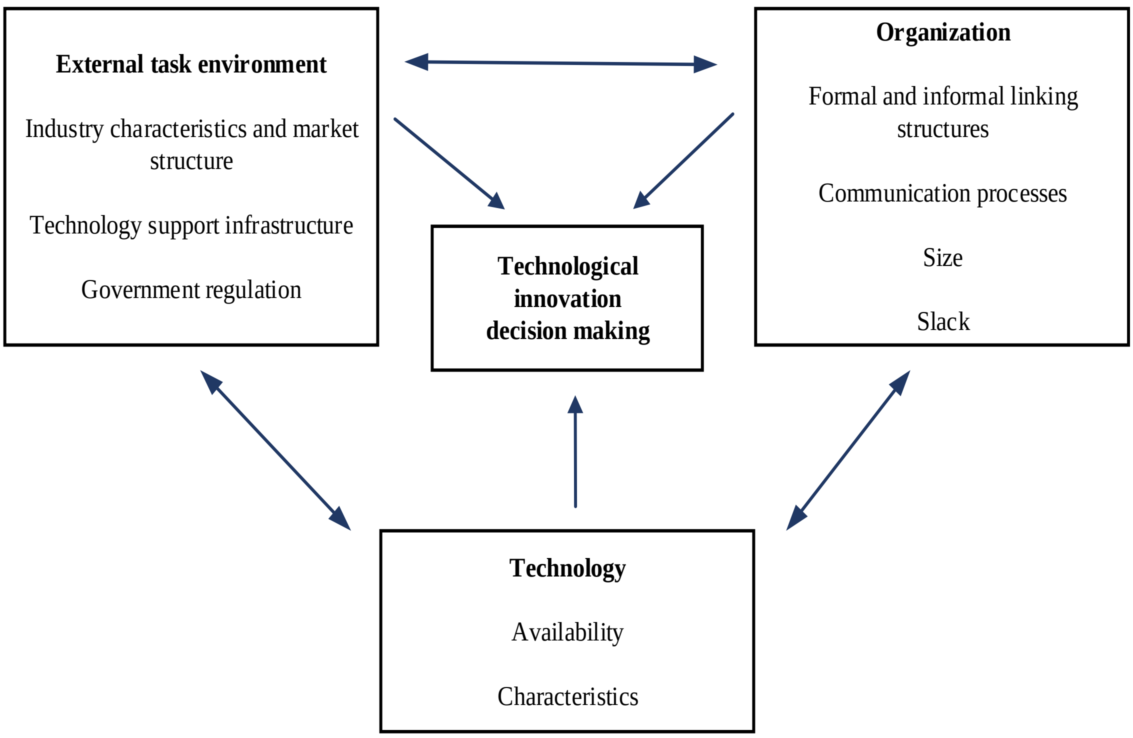

Figure 3.4: The technology, organization, and environment framework (Tornatzky et al., 1990)

The TOE framework is a useful analytical framework for different types of IS/IT adoption and assimilation (Oliveira and Martins, 2011). In addition, the TOE framework has a solid theoretical basis and consistent empirical support in the literature. Several authors applied TOE framework to understanding different IS adoptions like website (Oliveira and Martins, 2008), e-commerce (Teo et al., 2006), e-business (Zhu et al., 2003), open systems (Chau and Tam, 1997), ERP (Pan and Jang, 2008), and KMS (Lim, 2009). Oliveira and Martins (2011) presented a summary of studies applying the TOE framework to investigate IS adoption.

The literature has reported studies that have identified antecedents and determinants. Several studies focus on adopting enterprise systems like ERP, CRM, and BI&A. For instance, Ram and Pattinson (2009) identified information quality, system quality, organizational readiness, environmental assessment, and strategic value of IS as antecedents, as critical factors for ERP adoption success. These antecedents were further investigated to find out their contribution or role in achieving competitive advantage in ERP adoption (Ram et al., 2014). Hwang (2005) investigated ERP adoption by including two antecedents: uncertainty avoidance and perceived enjoyment as informal control mechanisms together (Kirsch, 1997). Other scholars went further and fully investigated both the internal and external antecedents from the business and technical perspective providing an impetus to consider ERP adoption (Bajwa et al., 2004). A recent study by Cruz-Jesus et al. (2019) developed a conceptual model using the TOE framework to assess antecedents positively influencing CRM adoption stages: evaluation, adoption, and routinization using data from 277 firms. These factors include data quality and integration, top management support, technology competence, and competitive pressure.

Pan and Jang (2008) examined the determinants in the TOE framework as factors affecting the decision to adopt ERP. Four factors were found to be important determinants of ERP adoption. These include technology readiness, size, perceived barriers, and production and operations improvements. Oliveira et al. (2014) also assessed the determinants as factors influencing the adoption of cloud computing in the manufacturing and service sectors. They developed a research model based on DOI theory and the TOE framework. These factors include security concerns, cost savings, relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, and regulatory support.

3.4 IS Adoption in SMEs

Traditional research in IS has primarily focused on large organizations. The adoption of IS by SMEs has generally received less attention from scholars (Premkumar, 2003). Similar to the early introduction of IS into large enterprises, the introduction of IS in SMEs tends to be fragmented and based on operational support and transaction processing (Blili and Raymond, 1993, Foong, 1999). Large enterprises are the ones reaping the early gains of IS (Levy et al., 2001). Traditionally, SMEs have been slow in adopting modern IS (Raymond, 1988). However, when the cost of IS falls and their use becomes mainstream, SMEs start to exploit IS potential (Levy et al., 2001).

With the advent of globalization, the successful adoption of IS will take on an increased significance for the survival, growth, and competitiveness of SMEs (Raymond and Uwizeyemungu, 2007). SMEs use knowledge to manage day-to-day operations. The problems, opportunities, and management issues encountered by SMEs in the IS adoption area are unique (Premkumar, 2003). The IS adopted by SMEs tends to be simple with a focus on transaction processing systems. Many organizations view an investment in IS not only as a means of cost reduction but also as a way to achieve business value (Levy et al., 1999). However, most SMEs that view IS as a cost has failed to recognize the potential of IS to change their business (Levy et al., 2003). There are some SMEs who are not reluctant to invest in IS after start-up—primarily those searching for growth. Generally, SMEs view IS investments in the way they view their production systems. Most SMEs expect IS to last a long time; therefore, they are unlikely to redevelop their systems (Levy and Powell, 1998).

IS investment in SMEs can be successful when it is either a low-cost investment for providing efficiency savings or the enabler of a value-added strategy (Levy et al., 2001). The former is for SMEs which do not have IS central to the business and the owner’s IS experience is limited. The latter is driven by the necessity of business growth. This reflects the two main purposes of IS adoption: cost reduction and adding value. Cost reduction represents the traditional use of IS based on their incremental and reactive adoption. Value-adding focuses on IS adoption for competitiveness, a possible source of success differentiation for SMEs (Yetton et al., 1994). Furthermore, the assumption that SMEs are “scaled-down” versions of large enterprises has been successfully challenged in literature, with widespread acceptance that small businesses are not just “little big businesses” (Hill et al., 2002, Dandridge, 1979). Thus, adopting IS innovations in SMEs cannot be a miniaturized version of large enterprises (Dwivedi et al. 2009). Due to the unique characteristics of SMEs, the need to examine IS adoption in SMEs is more crucial (Thong, 1999).

Several studies have applied the TOE framework in different IS adoptions in SME like e-commerce (Rahayu and Day, 2015, Rowe et al., 2012), cloud computing (Alshamaila et al., 2013), ERP (Raymond and Uwizeyemungu, 2007), and CRM (Jones et al. 2013). Several studies on adopting enterprise systems like ERP and CRM indicated there are several different factors influencing IS adoption in SMEs. Dwivedi et al. (2009) investigated factors influencing SME adoption of a set of enterprise systems (i.e., ERP, CRM, SCM). The results of their study revealed the factors influencing SME adoption of enterprise systems are different from the factors influencing SME adoption of other previously studied IS innovations. SMEs are more influenced by technological and organizational factors than environmental factors. Moreover, the results indicated SMEs have a greater perceived relative advantage, a greater ability to experiment with these systems before adoption, greater top management support, and greater organizational readiness. They also predicted that most SMEs could become adopters of enterprise systems. However, this study failed to differentiate between factors influencing each of these systems. Caldeira and Ward (2002) identified factors enabling and inhibiting the adoption and use of IS in SMEs (Table 3.1). They also investigated how these factors interrelate to determine relative success in IS adoption and use.

Several studies identified antecedents for IS adoption in SMEs. Elbertsen et al. (2006) provided insight into the antecedents of ERP adoption, including complexity, compatibility, IT competence, market efforts, and company size. Peltier et al. (2009) investigated the antecedents influencing CRM adoption by small businesses. These antecedents focused on environmental factors (market uncertainty and environmental hostility), technological characteristics (relative advantage and switching costs), and owner and organizational characteristics (product class knowledge, attitude towards change, age, education, years in business, and firm size).

Table 3.1: The success factors in IS adoption (Caldeira and Ward, 2002)

Internal Context	Financial resource availability
	Human resources
	Management perspectives and attitudes towards IS
	IS competencies
	Power relationships
	Users attitudes to IS use
	Position of the IS manager in the organizational structure
External Context	IS vendor’s support
	IS external expertise available
	Quality of the software available in the market
	Business pressure to adopt and use IS
Process	People involved
	Frameworks and techniques and used in IS development
	IS training
	Stages followed in IS development
Context	Type of IS solutions available in the firm
	Objectives and assumptions about IS
	Evaluation of IS benefits
	Time of adoption

Other scholars identified and validated factors influencing CRM adoption in SMEs (Alshawi et al., 2011). These factors were classified into three main factor groups: organizational, technical, and data quality factors. Organizational factors are those relating directly or indirectly to the structural, operational, human, and managerial sides of the SME business entity, like benefits, staff IT skills, managerial IT skills, firm size, etc. The technical factors refer to factors related to the soft and hard aspects of the IS/IT technology being adopted. These factors include infrastructure, implementation costs, system evaluation, software selection criteria, etc. Lastly, data quality factors refer to factors related directly to the concept of data quality. Factors like management characteristics, organizational characteristics, and management perception of CRM technology also influenced CRM adoption in SMEs (Newby et al., 2014).

Organizational readiness is also an antecedent to technological innovation (Tsai and Tang, 2012). Scholars have identified dimensions to be assessed to determine organizational readiness at the adoption stage. Prior research highlighted the importance of technical and organizational capabilities before the implementation process began and for being able to select the most suitable implementation strategy (Capaldo and Rippa, 2009). Top management should closely examine the current level of their organizations before contemplating the implementation of an ERP system in SMEs (Raymond and Uwizeyemungu, 2007). An organization possessing organizational readiness during IS implementation and use can achieve adoption success (Sammon and Adam, 2010).

3.5 BI&A Adoption

To better understand and examine BI&A adoption, several studies employed a wide range of theories, frameworks, and models. The most adopted theories, frameworks, models according to a recent review of BI&A adoption, are DeLone and McLean's (D&M) IS success model, the TAM model, and the DOI theory (Ain et al., 2019). For instance, the D&M's IS success model and TAM model were used to investigate how to design BI&A systems to improve BI&A adoption and use (Foshay et al., 2014). A framework based on D&M's IS success was proposed to identify the relationships between end user computing satisfaction, system usage, and individual performance in BI&A adoption (Hou, 2012).

The DOI theory is also adopted in a number of studies in BI&A literature. Ahmad et al. (2016) applied DOI theory to investigate BI&A characteristics influencing its successful adoption. Jaklič et al. (2018) adopted DOI to examine the interrelated role of compatibility in predicting BI&A use intentions. Yoon et al. (2014) identified factors affecting decisions to adopt BI&A at the individual level, which is drawn upon various theories, including DOI theory. The adoption rates of other theories in BI&A adoption research like RBV, TOE framework, and the UTAUT were relatively low (Ain et al., 2019). For instance, the TOE framework was applied to examine factors influencing BI&A usage in South African organization (Lautenbach et al., 2017) and to understand the determinants of BI&A system adoption stages (Puklavec et al., 2018, Puklavec et al., 2014).

BI&A literature has identified numerous factors influencing BI&A adoption. Three main factor categories have been identified: the organizational, IS, and user perspectives (Ain et al., 2019). First, the organizational perspective focuses on how the alignment of organizational goals, strategies, plans, and priorities with BI&A affects other systems. This category includes organizational-related factors like management support (Kohnke et al., 2011), competitive pressure (Boonsiritomachai et al., 2016), culture (Puklavec et al., 2014), and organizational readiness (Puklavec et al., 2014). Second, the IS perspective demonstrates the impact of IS-related factors like information quality (Nelson et al., 2005), system quality (Trieu et al., 2018), and IT infrastructure (Torres et al., 2018). This category emphasizes the importance of a scalable and flexible IT infrastructure and easy to use system interface and high-quality data and source system for BI&A. Lastly, the user's perspective focuses on human-related factors like IT knowledge and technical skills (Elbashir et al., 2013), user involvement (Kulkarni and Robles-Flores, 2013), and loss of power (Popovič, 2017). Table 3.2 depicts the factors in all three main categories. A summary of the key factors in these categories is presented in the study by Ain et al. (2019).

Table 3.2: Three main categories of factors influencing BI&A adoption (Ain et al., 2019)

Organizational perspective	Management support
	Champion
	Support and training
	Culture
	Social influence
	Resources
	Change management
	Facilitation conditions
	Organization size
	Service quality
	Well-defined vision and goals, BI & business strategy alignment, effective communication, effective project management, teamwork & composition, agile values, plan driven aspects
	Competitive pressure
	Structural empowerment
	BI management
	Organizational data environment, organizational readiness, external support
	User participation
	Organizational learning climate
	Organizational BI capabilities
	Top management commitment
	Knowledge sharing, technology driven strategy
IS perspective	Information/data quality
	System quality
	Perceived ease of use
	Result demonstrability
	Perceived usefulness
	Relative advantage
	Job relevance
	BI system maturity, BIS effectiveness
	Comprehensiveness of usage
	Compatibility
	Performance expectancy, effort expectancy

	IT infrastructure, integration
	Information and analysis usage, Technical readiness of BI
	Integration with other systems, user access
	BI system dependence
	BI system infusion
	Management capability, sensing capability, seizing capability, business process change capability
	Functional performance
	Impact on marketing & Sales, Impact on management and internal operations, Impact on procurement
	Technological BI capabilities – data source, data type, data reliability, interaction with other systems, user access
Users perspective	Anxiety
	Absorptive capacity
	Team IT knowledge and technical skills
	Self-efficacy
	User involvement
	Personal innovativeness
	Loss of power, changes in decision-making approach, job/skills change
	Conscientiousness, emotional stability, extraversion, openness to experience

Beside the factors influencing BI&A adoption, organizations face few challenges in BI&A adoption. One of these challenges is the manager's resistance to using BI&A systems resulting in low system acceptance (Chang et al., 2015b). Another challenge is the lack of motivation to use the BI&A systems caused by a lack of capabilities or ability to explore the systems (Seah et al., 2010). Other challenges also include the fear of losing power over information (Popovič, 2017), system issues (Olszak, 2016), and insufficient communication between IT and business (Richards et al., 2019). In addition, there are seven identified emergent constructs of system use, problems, and causes: reporting, data, workflow, role authorization, users' lack of knowledge, system error, and user-system interaction (Deng and Chi, 2012). The list of challenges is also summarized in the literature (Ain et al., 2019).

Organizational readiness was highlighted as an important factor contributing to the success of IS adoption. This factor has also been depicted as a prerequisite for the success of BI&A adoption (Williams and Williams, 2010). However, few studies in BI&A literature have provided an overview of factors to assess BI&A readiness. Prior research presented seven factors to affect whether BI&A investment will provide profits to an organization or not (Williams and Williams, 2010). These factors are called readiness factors, including (1) strategic alignment, (2) continuous process improvement culture, (3) culture for using information and analytical applications, (4) BI portfolio management, (5) decision process engineering culture, (6) BI and data warehousing technical readiness, and (7) effective business and IT partnership. Other scholars focused on management's role in BI&A readiness and presented seven dimensions (Anjariny and Zeki, 2014). These seven dimensions to consider in assessing BI&A readiness include: (1) management-related dimension, (2) business-related dimension, (3) infrastructure, (4) user-related dimension, (5) project-related dimension, (6) teamwork, and (7) data.

The importance of management-related dimension was highlighted in the literature (Anjariny and Zeki, 2014). This dimension deals with management decisions on resource commitment to funding, project champion, and sponsors. Thus, it underlines the importance of top management support for the BI&A project. The business-related dimension includes readiness factors like having clear vision, building business case, and an organization's ability to measure BI&A business value are explicitly highlighted (Anjariny and Zeki, 2014). Moreover, the infrastructure dimension includes the technical framework, functionality, and usability. The importance of including users to improve BI&A commitment was also emphasized. The user-related dimensions include the participation, education, and commitment of the BI&A users. The project-related dimension is about the delivery approach, planning, and scope of the BI&A project. Teamwork dimension illustrates the importance of skills, consultants, and expertise. Data dimension demonstrates data quality significance knowing the consequences of poor data before BI&A adoption.

Other scholars identified critical success factors (CSFs) in BI&A adoption. For instance, a study by Yeoh and Koronios (2010) identified seven CSFs for BI&A adoption: (1) committed management support and sponsorship, (2) clear vision and well-established business case, (3) business-centric championship and balanced team position, (4) business-driven and iterative development approach (5) user-oriented change management, (6) business-driven, scalable and flexible technical framework, (7) sustainable data quality and integrity. Moreover, the authors argued that the common reason for BI&A failure is the absence of alignment between BI&A initiatives and business vision, resulting in the failure to support the business objectives. Therefore, the strong link between the business vision and BI&A adoption in building a well-established business case was highlighted (Yeoh and Koronios, 2010). A total of 60 CSFs were identified through a content analysis approach from 11 papers (Hawking and Sellitto, 2010). The most common of these CSFs are management support, user participation, and team skills.

3.6 BI&A Adoption in SMEs

There is a small stream of research on BI&A adoption in SMEs. Although SMEs have as much need for BI&A as large enterprises (Cheung and Li, 2012), SMEs lag behind the proliferation of BI&A (Boonsiritomachai et al., 2016, Grabova et al., 2010).

The BI&A adoption theories are crucial to understanding the factors affecting BI&A adoption. Hatta et al. (2015) reviewed the literature to identify factors influencing BI&A adoption in SMEs. They also reported on using adoption theories in the BI&A literature and discussed two prominent adoption models in the SME context: the DOI theory and the TOE framework. Hatta et al. (2015) then created an integrated adoption model comprising 25 drivers. Further, they combined their findings into four main categories based on the DOI theory and the TOE framework. The four main categories are: technological context (internal and external), organizational context (size, structure, managerial structure, and human resources), environmental context (competitors and regulatory environment), and CEO's innovativeness context (decision-making, willingness to adopt IS to improve organizational performance). Moreover, a BI&A maturity model based on DOI theory was proposed to distinguish the different BI&A maturity levels in Thai SMEs (Boonsiritomachai et al., 2016). In addition, different factors influencing BI&A adoption are also presented. These factors include relative advantage, complexity, compatibility, absorptive capacity, organizational resource availability, competitive pressure, vendor selection, owner-managers' innovativeness, and owner-managers' IT knowledge. Other scholars have developed and empirically tested a conceptual model based on DOI for assessing the impact of BI&A use on firm performance in SME context (Popovič et al., 2019).

Puklavec et al. (2014) also reviewed the literature to identify determinants influencing BI&A adoption in SMEs at the firm level. They also conducted qualitative interviews to provide a succinct list of determinants for BI&A adoption: establish management support, perception of strategic value, project champion, organizational data, and organizational readiness. Puklavec and colleagues argued the list of determinants will guide both the development and testing of BI&A frameworks in SMEs. Coupling the TOE framework with the DOI model, the same authors did a study to provide a better understanding of BI&A adoption determinants (Puklavec et al., 2018). Gibson and Arnott (2003) conducted a review to explore the lack of BI&A use in SMEs and presented ten characteristics affecting the adoption of BI&A. They emphasized the importance of the innovativeness of owner-managers. Gibson and Arnott (2003) argued innovative owner-managers are more likely to use BI&A for decision-making, know the business value of BI&A, have enough resources for BI&A, and understand the importance of aligning BI&A with business strategy.

A study by Chichti et al. (2016) applied the TOE framework and identified what determines BI&A adoption in Tunisian public organization when supporting SMEs. Due to SMEs' dynamic business environment, the environmental factors from the TOE framework are considered important in supporting SMEs. Moreover, strategic foresight was suggested to support SMEs in coping with competition (Chichti et al., 2016). Olszak and Ziemba (2012) identified CSFs for BI&A adoption in SMEs. They further expanded the list of CSFs proposed by Yeoh and Koronios (2010). The CSFs are support from senior management, skilled team, and competent BI&A project manager. A well-defined business problem and business process were highlighted as one of the most significant CSFs. Data quality, user-friendly systems, and integration between BI&A and other systems are CSFs in a more technological perspective. Qushem et al. (2017) also conducted a review and identified SME specific determinants for BI&A using the TOE framework.

There are few other adoption related issues discussed in the literature. Organizational readiness has been recognized as essential to achieving successful BI&A adoption in SMEs. Hidayanto et al. (2012) developed a framework to measure the readiness level of BI&A in SMEs. They used BI&A experts to identify the most important factors hindering BI&A readiness. Three CSFs are more important than others: management support and sponsorship, clear vision and well-established business case, and strategic alignment. Moreover, Hidayanto et al. (2012) demonstrated how these factors could be used to measure BI&A readiness without providing suggestions on how to achieve these factors. Some factors identified in Hidayanto et al.'s framework was based on Williams and Williams (2010). Puklavec et al. (2014) also identified BI&A readiness as an important factor for SMEs without explicit explanation of what readiness means. A study by Gudfinnsson and Strand (2017) explored the challenges faced by SMEs in BI&A adoption through a case study of four SMEs. The examples of these challenges are a lack of BI&A skills, limited interest from executives and owners on using BI&A, lack of skills to see BI&A value, and data quality issues. Hill and Scott (2004) conducted a qualitative study and proposed a set of recommendations for successful BI&A adoption. They illustrated up-to-date information and personal contacts as challenges in BI&A adoption. Moreover, Sadok and Lesca (2009) identified seven necessary acceptance conditions to facilitate organizational changes in SME BI&A adoption. Further, Scholz et al. (2010) explored both the perceived benefits and challenges in BI&A adoption in German SMEs.

4 Research Approach

This chapter presents the overall vision of the research approach applied in this study. Chapter 4.1 provides an overview of the research design followed by the process of recruiting the informants in Chapter 4.2. I provide data collection details for the Delphi study and qualitative interviews in Chapter 4.3, report on data analysis in Chapter 4.4, and assess the research quality in Chapter 4.5.

4.1 Research Design

Research design is the logical sequence connecting empirical data to a study's initial research questions and conclusions (Yin, 2017). According to De Vaus (2001), the research design's function is to ensure that the evidence obtained enables us to answer the initial question as unambiguously as possible. When designing a research, the researcher must consider an important question: what evidence is needed to answer the research question convincingly? The research design could be viewed as a "blueprint" for dealing with four issues: what to study, what data is relevant, what data to collect, and how to analyze the research (Philliber et al., 1980).

Interpretivism is concerned with sense making and understanding (Gioia and Chittipeddi, 1991). The ontological assumption of interpretivism is an objective social reality does not exist, but rather is produced and reproduced among humans through their interactions (Orlikowski and Baroudi, 1991). The knowledge of BI&A adoption, decisions to invest, implement, utilize, and create value from BI&A investments are socially constructed by people and organizations. Thus, BI&A is related to people and social settings in general. The aim of interpretive research is to "understand phenomena through accessing the meaning that participants assign to them (Orlikowski and Baroudi, 1991, p. 5)." The epistemological position of interpretivism is subjective (Scotland, 2012). I decided to acquire BI&A adoption knowledge based on interpretations of experts involved in my study.

I approached the study by first conducting a systematic literature review to collect, analyze, and synthesize all extant literature in the interest domain. This review resulted in Paper 1, the first publication in this thesis. 62 articles were reviewed and categorized using the concept-centric method. Other dimensions like publication source, publication year, citation status, and research method were considered in the literature review analysis. This review presented the current state of research topics on this domain. At the same time, it also revealed prospective gaps with implications on all the succeeding publications and offered guidance on suggesting future research avenues. The review also contributed to refining the problem definition in this thesis. As shown in Figure 4.1, an extended literature review was conducted to further develop Paper 1. By following the same method from the first review conducted in 2016, 78 articles were identified in this extended review. Therefore, the extended literature review conducted in 2017 was considered the official literature review publication in this thesis.

Second, a ranking type Delphi study was conducted to better understand BI&A adoption in SMEs based on the issues identified and prioritized by BI&A experts (Okoli and Pawlowski, 2004, Pare et al., 2013). This resulted in Paper 5. For decades, the Delphi method has been applied in various fields and considered an established and legitimate research method (Dalkey and Helmer, 1963). It is a means and method for consensus-building using a series of questionnaires to collect data from a panel of selected subjects (Linstone and Turoff, 1975). This method involves the following phases: assembling experts, brainstorming, narrowing-down, two rounds of ranking (Pare et al., 2013) and follow-up interviews (Day and Bobeva, 2005). The results of the Delphi study addressed SQ2.

Last, a qualitative interview using the expert interview technique by Meuser and Nagel (2009) was conducted. This resulted in Papers 2, 3, and 4, which are all exploratory studies. Meuser and Nagel (2009) defined the expert interview approach as a method of qualitative empirical research designed to explore expert knowledge. Thus, this method enabled this thesis to be grounded in current practice and provides rich and in-depth information regarding the interest domain. The outcomes of the exploratory studies addressed SQ1 and SQ3.

The research design in this thesis comprises several activities. These include the literature review, problem definition, data collection, research articles, and thesis summary with the specified estimated time frame for each activity. A research activities overview is in Figure 4.1.

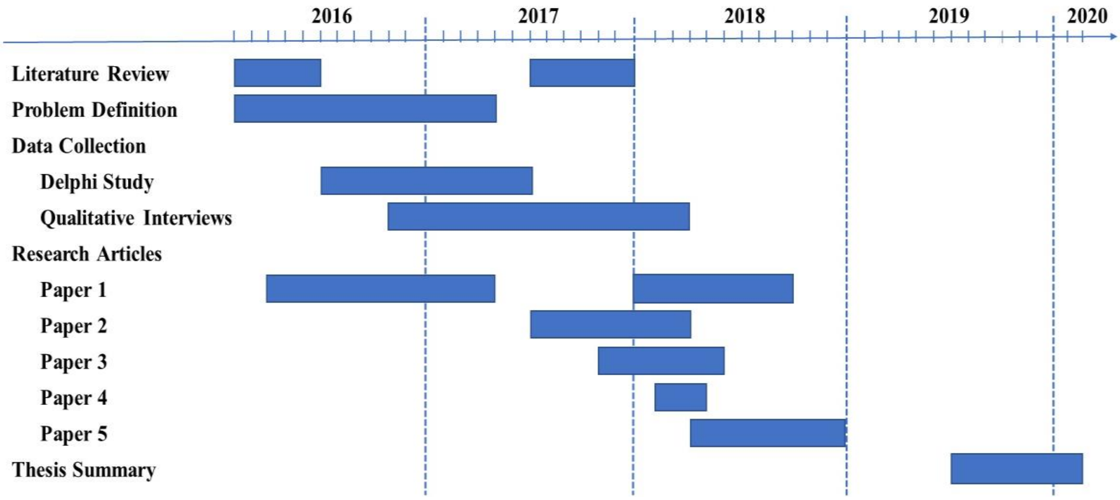

Figure 4.1: Overview of research activities

4.2 Getting Informants on Board

As mentioned above, the first empirical study in this thesis is the Delphi study followed by the qualitative interview. Conducting these empirical studies involves recruiting informants. Bygstad and Munkvold (2011) have explored the role of informants in case study research in IS. They defined informants as stakeholders giving qualified information or opinions on a case. Similarly, Yin (2017) defined informant as a study subject providing critical information or interpretations about the interest domain, and suggest other evidence sources.

LinkedIn is a heavily used professional business networking site and one of the largest professional matchmaking sites in the world (Van Dijck, 2013). To identify prospective participants, LinkedIn was used to search for informants to participate in the Delphi study. The snowballing technique was also used, where each informant was asked to suggest another informant. The composition and selection of informants or experts are of utmost importance to achieve the successful execution of a Delphi study (Linstone and Turoff, 1975). Both the expertise and quality of the experts are crucial to improve the credibility and validity of the process (Hsu and Sandford, 2007, Okoli and Pawlowski, 2004). By using LinkedIn, the informant's present job position and former experiences in BI&A became available. As suggested by Keil et al. (2013), both compulsory and desired criteria were defined to assure high-quality experts. The compulsory criteria include a minimum of five years of BI&A expertise, first-hand experience in Norwegian SMEs, and willingness to participate in the entire study. Desired criteria include working experience in a consulting company, attendance at a BI&A conference, and participation in BI&A forums or being active in other BI&A events in Norway. The invitation letter and a Delphi study information sheet were sent to 190 experts through LinkedIn messaging and work e-mail. Some experts denied the invitation due to a tight working schedule or not having enough experience with SMEs. Others did not respond at all. The Delphi study recruited a total of 43 experts (Table 4.1). Most experts are between 35 to 45 years of age and have more than 10 years of experience from leading or participating in BI&A projects, having either deployed, adapted, or utilized BI&A systems. Moreover, the experts are from a wide range of industries representing both vendor and user organizations of BI&A. After the experts agreed to participate, an email containing Delphi study time plan was sent to them.

Table 4.1: Delphi study informant's profile

No.	Position	Gender	Educational Attainment	Years of experience	Found through	Industry	Sector
1	BI Consultant	M	BSc	10	LinkedIn	IT Consultancy	Private
2	Head of BI	M	MSc	6	LinkedIn	IT Consultancy	Private
3	BI Advisor	M	MSc	11	LinkedIn	Aquaculture	Private
4	BI Consultant	M	BSc	15	LinkedIn	BI Consulting	Private
5	BI Manager	M	MSc	10	LinkedIn	Food and Beverages	Private
6	BI Consultant	M	MSc	20	LinkedIn	IT Consultancy	Private
7	Head of BI	M	MSc	11	LinkedIn	IT Consultancy	Private
8	BI Consultant	M	MSc	9	Snowballing	IT Consultancy	Private
9	Head of BI	M	BSc	16	LinkedIn	Chemicals	Private
10	BI Consultant	M	BSc	10	LinkedIn	IT Consultancy	Private
11	Head of BI	F	BSc	15	LinkedIn	IT Consultancy	Private
12	BI Consultant	M	MSc	6	LinkedIn	IT Consultancy	Private
13	BI Manager	M	BSc	12	LinkedIn	IT Consultancy	Private
14	BI Architect	M	BSc	10	LinkedIn	BI Consulting	Private
15	BI Architect	M	BSc	17	LinkedIn	Insurance	Private
16	BI Consultant	F	BSc	7	LinkedIn	IT Consultancy	Private
17	BI Architect	M	MSc	10	LinkedIn	IT Consultancy	Private
18	CEO	M	BSc	17	LinkedIn	IT Consultancy	Private
19	Head of BI	M	BSc	15	LinkedIn	Aviation	Private
20	BI Consultant	F	BSc	10	Snowballing	Electric Power	Private
21	BI Consultant	M	BSc	8	LinkedIn	IT Consultancy	Private
22	Head of BI	M	BSc	15	LinkedIn	Banking	Private
23	BI Architect	M	BSc	15	LinkedIn	IT Consultancy	Private
24	BI Advisor	M	MSc	7	LinkedIn	Investment & Consulting	Private
25	Data Scientist	M	MSc	6	LinkedIn	BI Software Provider	Private

No.	Position	Gender	Educational Attainment	Years of experience	Found through	Industry	Sector
26	BI Consultant	M	MSc	10	LinkedIn	IT Consultancy	Private
27	Head of BI	M	BSc	30	LinkedIn	BI Consulting	Private
28	BI Consultant	M	MSc	8	LinkedIn	IT Consultancy	Private
29	BI Consultant	M	MSc	5	LinkedIn	IT Consultancy	Private
30	BI Consultant	M	BSc	7	LinkedIn	IT Consultancy	Private
31	BI Manager	M	MSc	10	Snowballing	Consulting & Advisory	Private
32	BI Advisor	M	BSc	20	Snowballing	IT Consultancy	Private
33	BI Consultant	M	BSc	10	Snowballing	IT Consultancy	Private
34	Head of BI	M	BSc	10	LinkedIn	IT Consultancy	Private
35	BI Architect	F	MSc	12	Snowballing	Banking	Private
36	Data Governance Leader	F	BSc	13	Snowballing	Banking	Private
37	Data Scientist	M	MSc	6	Snowballing	IT Consultancy	Private
38	Associate Professor	F	PhD	10	Snowballing	Academics	Private
39	BI Advisor	F	MSc	10	Snowballing	IT Consultancy	Private
40	BI Consultant	F	MSc	12	Snowballing	IT Consultancy	Private
41	BI Consultant	F	MSc	12	Snowballing	IT Consultancy	Private
42	BI Architect	F	BSc	18	LinkedIn	IT Consultancy	Private
43	BI Advisor	M	BSc	17	Snowballing	BI Software Provider	Private

There were 15 informants participated in both the Delphi study and the qualitative interview. To recruit more informants, the snowballing technique was again used. I also joined and was the guest speaker at a BI&A forum in Oslo in October 2017. During the BI&A forum, various BI&A professionals, like consultants, architects, vendors, heads of BI&A, and data scientists showed interest in my PhD study. There were 38 informants in total taking part in the qualitative study. I had more than one interview with some informants eager to share their experience. This resulted in a total of 46 interviews. Table 4.2 provides more information about the informants and each interview's length.

Table 4.2: Informant's profile

No.	Position	Gender	Found through	Industry	Sector	Duration of interview (in minutes)
1	BI Consultant	M	Delphi	IT Consultancy	Private	31 (Paper2)
2	BI Consultant	M	Delphi	IT Consultancy	Private	30 (Paper2)
3	BI Consultant	M	Delphi	IT Consultancy	Private	30 (Paper2)
4	BI Consultant	M	Delphi	IT Consultancy	Private	30 (Paper2) + 35 (Paper3)
5	BI Consultant	M	Delphi	Oil & Gas	Private	75 (Paper2 & 4)

No.	Position	Gender	Found through	Industry	Sector	Duration of interview (in minutes)
6	BI Advisor	M	Delphi	IT Consultancy	Private	120 (Paper2 & 4) +40 (Paper3)
7	BI Advisor	M	Delphi	Investment & Consulting	Private	40 (Paper2) + 45 (Paper3)
8	BI User	M	Snowballing	Food & Beverages	Private	45 (Paper2)
9	BI User	M	Snowballing	Chemicals	Private	30 (Paper2)
10	Head of BI	M	Delphi	IT Consultancy	Private	34 (Paper2)
11	Head of BI	M	Delphi	Chemicals	Private	43(Paper2)
12	Head of BI	M	Delphi	IT Consultancy	Private	60 (Paper2 & 4) + 35 (Paper3)
13	Head of BI	M	Snowballing	IT Consultancy	Private	60 (Paper2) + 30 (Paper3)
14	Head of BI	M	Snowballing	Insurance	Private	47 (Paper2)
15	Head of BI	M	Delphi	Banking	Private	46 (Paper2) + 40 (Paper3)
16	Head of BI	M	Delphi	BI Consulting	Private	40 (Paper2)
17	Data Scientist	M	Delphi	BI Software Provider	Private	33 (Paper2)
18	Data Scientist	M	Snowballing	Insurance	Private	37 (Paper2)
19	Data Scientist	F	Snowballing	IT Consultancy	Private	30 (Paper2)
20	Data Scientist	M	BI Forum	IT Consultancy	Private	83 (Paper2 & 4) +40 (Paper3)
21	Data Scientist	M	Snowballing	Banking	Private	31 (Paper2)
22	BI Vendor	M	Delphi	BI Software Provider	Private	55 (Paper2)
23	BI Advisor/Vendor	M	BI Forum	Consulting and Advisory	Private	115 (Paper2 & 4)
24	Data Governance Leader	F	Delphi	Banking	Private	73 (Paper2 & 4) + 30 (Paper3)
25	Head of Analytics	M	Snowballing	Insurance	Private	33 (Paper4)
26	Head of Analytics	F	Snowballing	Public Welfare	Public	35 (Paper4)
27	Data Manager	M	Snowballing	BI Software Provider	Private	37 (Paper4)
28	Head of Data Warehouse	M	Snowballing	IT Consultancy	Private	36 (Paper4)
29	Data Scientist	M	BI Forum	IT Consultancy	Private	30 (Paper4)
30	BA Consultant	M	Snowballing	Insurance	Private	40 (Paper4)
31	BI project Manager	F	Snowballing	IT Consultancy	Private	40 (Paper3)
32	Data Scientist	M	BI Forum	IT Consultancy	Private	35 (Paper3)
33	BI Architect	M	BI Forum	Banking	Private	32 (Paper3)
34	BI Architect	M	Snowballing	IT Consultancy	Private	30 (Paper3)
35	Head of BI	M	Snowballing	Agricultural	Private	30 (Paper3)
36	Head of Analytics	F	BI Forum	IT Consultancy	Private	30 (Paper3)
37	Head of Analytics	F	BI Forum	IT Consultancy	Private	35 (Paper3)
38	Head of Analytics	M	Snowballing	Consulting and Advisory Services	Private	45 (Paper3)

4.3 Data Collection

The data collection techniques involved conducting a grounded Delphi study with follow-up and qualitative interviews using the expert interview method. Each technique is detailed below.

4.3.1 Qualitative Interviews

The qualitative interviews were the primary data source in this thesis. The expert interview technique by Meuser and Nagel (2009) was used to conduct semi-structured interviews with BI&A experts from various industries in Norway. This approach is a method of qualitative empirical research designed to explore expert knowledge (Meuser and Nagel, 2009). Thus, this method was chosen as this enables this thesis to be grounded in current practice and the method provides rich and in-depth information regarding the interest domain. The semi-structured interview method was selected to offer the merit of using a list of predetermined themes in a structured interview while ensuring adequate flexibility to enable the interviewee to talk freely about any topic in the interview.

In total, 46 interviews were conducted with 38 informants. The data collection took place from October 2016 through March 2018 (Figure 4.1). Out of 38 informants, 15 are experts who participated in the Delphi study. Each interview lasted about 30-120 minutes and was carried out primarily through face-to-face meetings or by telephone. In exploratory research, personal interviews are recommended because they allow comprehensive discussions. The interviews were held mostly in English, with Norwegian statements translated into English. The questions were mainly open-ended, so the informants had the possibility to explore their experiences and views (Yin, 2017).

At the beginning of each interview, the informants were asked to briefly describe how they currently work with BI&A. In addition, they were provided with the status of SME BI&A adoption according to the literature. The focus of the interviews varied depending on the interviewees' professions. The main purpose of conducting the interviews was to explore BI&A adoption in Norwegian SMEs and to obtain a better understanding of BI&A adoption. The interview guide was developed and focused explicitly on implementation, utilization, and value creation of SME BI&A (Appendix A).

All informants consented to having their interview recorded. Some interesting issues mentioned in the interview were written down. However, the notetaking never disrupted the interview's conversation flow. Immediately after the interviews, the notes were reviewed to identify what important points were made. Any clarification was done by e-mail and telephone communication.

4.3.2 Delphi Study

The Delphi technique is designed as a group communication process aiming to collect opinions and discussions of experts on a particular subject (Yousuf, 2007). As Hsu and Sandford (2007) stated, "Common surveys try to identify 'what is,' whereas the Delphi technique attempts to address 'what could/should be (p. 1).'" Thus, this method will appropriately reach the goal of this study. The purpose of the Delphi study is to generate a list of drivers and inhibitors identified and prioritized by experts in SME BI&A adoption. This is accomplished by gaining consensus on the lists of drivers and inhibitors among BI&A experts. These drivers and inhibitors can be beneficial for practitioners who embark on, lead, and participate in BI&A projects.

The Delphi study was applied in close cooperation with my supervisors. They were actively involved through the design, data collection, data analysis of the Delphi results, and follow-up interviews. To ensure the study's validity and credibility, it was designed based on the principles and guidelines found in the Delphi literature (Okoli and Pawlowski, 2004, Day and Bobeva, 2005, Keil et al., 2013, Hsu and Sandford, 2007). Communication with experts was done mainly through email correspondence for convenience. The study took four rounds: brainstorming, narrowing down, and two rounds of ranking (Okoli and Pawlowski, 2004). After the first round, the experts were asked to validate the list of SME BI&A adoption factors before continuing the study in the next round. Follow-up interviews were also conducted with 12 BI&A experts participating in the Delphi study. Delphi studies can benefit from follow-up interviews with experts by gaining elaborations of the selected list of items (Day and Bobeva, 2005, Keil et al., 2013). The interviews' purpose was to gain an in-depth understanding of why experts considered some items to be more important than others. Figure 4.2 depicts the Delphi study process and follow-up interviews.

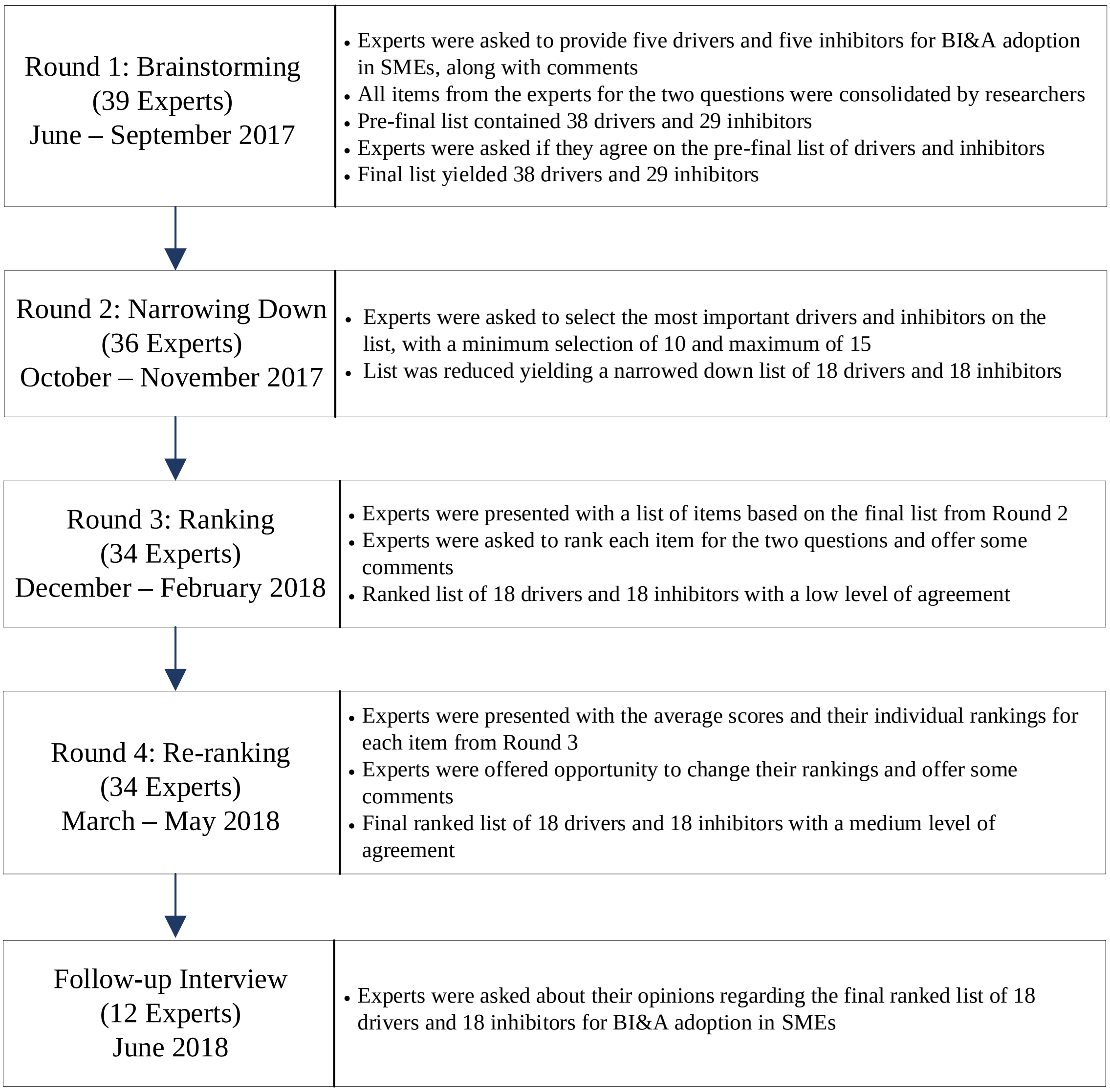

Figure 4.2: Summary of the Delphi phases and follow-up interviews

The anonymity of the Delphi study allows the panelists to freely express their opinions without undue social pressures to conform to others in the group. All the surveys were sent separately through email to ensure full anonymity. The Delphi study's design choices are summarized in Table 4.3.

Table 4.3: Delphi study design

Criteria	**Choice**
Purpose of the study	Identification of factors influencing BI&A adoption in SMEs
Number of rounds	4 rounds and follow-up interviews with some of the experts
Criteria for Delphi panel	Experts on BI&A adoption with extensive experience of minimum 5 years
Mode of operation	Remote access
Anonymity of the panel	Full
Communication media	Computerized (i.e., e-mail)
Concurrency of rounds	Sequential set of rounds (brainstorming, narrowing down, and two rankings)

The first round of the Delphi process traditionally begins with an open-ended questionnaire (Hsu and Sandford, 2007) which serves as the cornerstone of soliciting specific information about a content area from the Delphi subjects (Custer et al., 1999). It is also acceptable in the Delphi process to use a structured first round questionnaire. The first round is brainstorming, where two questions gained knowledge about factors influencing BI&A adoption: (*1) What are the drivers (different factors contributing to adoption) of SME BI&A adoption? (2) What are the inhibitors (challenges, problems) of SME BI&A adoption?*

Together with these two questions, instructions on how to answer the questionnaire and the description of the study were attached to the Microsoft Word file. Each expert was asked to provide at least five items with supplementary comments for both drivers and inhibitors and, if possible, justify their importance.

The experts were given at least two weeks to answer the first questionnaire. Nearly half responded within a week. However, several reminders were sent to other experts before receiving the rest of the questionnaires. In this first round, four experts declined to participate due to workload issues. The 39 experts' responses to the first questionnaire were analyzed and the TOE framework was used to cluster the items into TOE categories. This resulted in a consolidated list of 38 drivers and 29 inhibitors (Table A1 and A2 in Paper 5). Hence, the experts validated the list to ensure all items were included and appropriately interpreted. Two weeks were given to experts to complete this task. Unfortunately, many experts needed more than two weeks due to workload and health issues. All experts successfully validated the lists with few comments to improve the clarification of items and help eradicate similar items. The list of drivers and inhibitors was accepted by experts and ready for the next round.

In the narrowing-down round, a randomly ranked list of the 67 items (38 drivers and 29 inhibitors) identified from the brainstorming round was sent to each expert. The experts were asked to select between a minimum of 10 and maximum of 15 important items from the lists of drivers and inhibitors. Each item on the list was provided with a brief description to ensure clarity before the selection. The purpose of this round was to reduce the two lists of items into a more manageable number of drivers and inhibitors before commencing the next round (Schmidt, 1997). The experts were given two weeks to complete this round. Few experts have asked for more time to complete the questionnaire. However, three experts were unable to participate in this round due to personal reasons. In total, 36 experts managed to complete this round.

In the ranking round, the experts were asked to randomly rank the arranged lists of items to decide on the relative importance of the items. The focus of this round was to rank the lists of 18 drivers and 18 inhibitors. The experts were given three weeks to complete this round. Two more experts did not manage to complete this round due to tight working schedules. Thus, the consensus of the 34 experts was measured by calculating the mean ranking and Kendall's coefficient of concordance (*W*) (Kendall and Gibbons, 1990). Unfortunately, the level of concordance of *W*=0.7 which is considered the high level of agreement for Delphi studies, was not reached at this round (Schmidt, 1997).

Another ranking round was performed to increase the value of Kendall's *W* values. In this re-ranking round, the average ranking of the items and their individual rankings from the first ranking round was distributed to the experts. In addition, experts were asked to review the average list of rankings and provided them opportunities to change their original rankings if they did not agree. The re-ranking round survey was created in Microsoft Excel with three sheets (Appendix A). The first sheet consists of both the instructions on completing the survey and the explanation of conducting another ranking round. The second and third sheets consist of the average rank list of 18 drivers and 18 inhibitors with comments, the original ranking of the expert, and a space for a new ranking if they do not agree. The experts were given three weeks to complete this round and all of them did.

Out of 34 experts, only three did not make any changes and stand by their original rankings. A moderate degree of consensus was reached after completing the re-ranking round. Despite not reaching the level of concordance of *W*=0.7, the re-ranking round was the last Delphi process round. According to the literature, the number of Delphi iterations can vary from three to five and largely depends on the degree of consensus sought by the investigators (Hsu and Sandford, 2007). Based on the last round, several experts showed less interest in another study round. Conducting a third ranking may decrease result validity.

The follow-up interviews with 12 experts participating in the Delphi study were conducted in June 2018. The goal was to utilize the findings of these follow-up interviews to gain an in-depth understanding of why experts considered some items to be more important than others. The experts were asked the following questions: *(1) What is your opinion of the final ranked lists of drivers and inhibitors? (2) Why are the top drivers and inhibitors important? Why are some items more important than others?* The semi-structured interviews were conducted either face-to-face or by phone, and each interview lasted about 15-25 minutes. Table 4.4 provides an overview of the follow-up interviews with 12 experts.

Table 4.4: Overview of the follow-up interviews for the Delphi Study

No.	Position	Gender	Industry	Sector	Duration of interview (in minutes)
1	BI Vendor	M	BI Software Provider	Private	25
2	BI Advisor	M	IT Consultancy	Private	20
3	BI Advisor	M	Investment Consulting	Private	15
4	BI Advisor	M	Aquaculture	Private	20
5	BI Consultant	M	IT Consultancy	Private	20
6	BI Consultant	M	BI Consulting	Private	15
7	BI Consultant	M	IT Consultancy	Private	18
8	BI Architect	M	BI Consulting	Private	22
9	Head of BI	M	IT Consultancy	Private	25
10	Head of BI	M	IT Consultancy	Private	20
11	Head of BI	M	BI Consulting	Private	21
12	Head of BI	M	IT Consultancy	Private	16

4.4 Data Analysis

For the Delphi study, all items generated by the experts from the first questionnaire were logged into a spreadsheet, discussed, and coded. The first round yielded 435 items, with 227 drivers and 208 inhibitors. Similar items were merged and combined, and duplicate meanings were removed. This resulted in 250 items (139 drivers and 111 inhibitors) grouped into the TOE categories. After applying the TOE framework, an additional combination and merging of the items resulted in 67 items, with 38 drivers and 29 inhibitors. This list of drivers and inhibitors were validated by the experts to ensure all items from the first round were included and appropriately interpreted.

Since the Delphi study's purpose was to improve the understanding and explore the factors influencing BI&A adoption in Norwegian SMEs, the study was not contextualized based on prior knowledge. Ideally, the study started with a broader scope on those items progressed with the response from and interviews with the panelists. Therefore, all items identified in this study have been contextualized by the panelists. One item related to General Data Protection Regulation was not included in the list during validation. Before continuing to the narrowing-down phase, a panelist suggested including the missing item (Figure 4.3). The rest of the panelists approved the lists of drivers and inhibitors in the validation phase.

Analyzing the responses in this narrowing-down phase involved calculating the percentage of total votes each item gained from the experts. The intention was to reduce the two lists of items into a more manageable number of drivers and inhibitors. In this respect, the items selected by more than 50% of the experts were selected for the ranking phase. Thus, the 38 drivers and 29 inhibitors were reduced to 18 drivers and 18 inhibitors.

The results from the ranking phase were analyzed by calculating the mean ranking and Kendall's coefficient of concordance (W) (Kendall and Gibbons, 1990). This was performed using Microsoft Excel. Kendall's W values were calculated to measure the consensus among experts. The Kendall method is the most popular method for measuring current agreement (the ordered list by mean ranks) with a least of squares solution, mainly due to its simplicity (Schmidt, 1997). The level of agreement among the panelists was below 0.7, which, according to Schmidt (1997), is a very weak agreement. The Kendall's W values were W=0.17 for drivers and W=0.23 for inhibitors.

The results from the re-ranking phase were also analyzed by calculating the mean ranking and Kendall's coefficient of concordance (W) using Microsoft Excel. Even though the highest level of agreement was not reached, the level of agreement improved in this phase. The Kendall's W values were W=0.47 for drivers and W=0.50 for inhibitors—a moderate level of agreement. The top 18 drivers and 18 inhibitors were sorted into a table along with their average. The tables clearly indicated the variations in the item rankings between the first and second rounds (Table 2 and 3 in Paper 5).

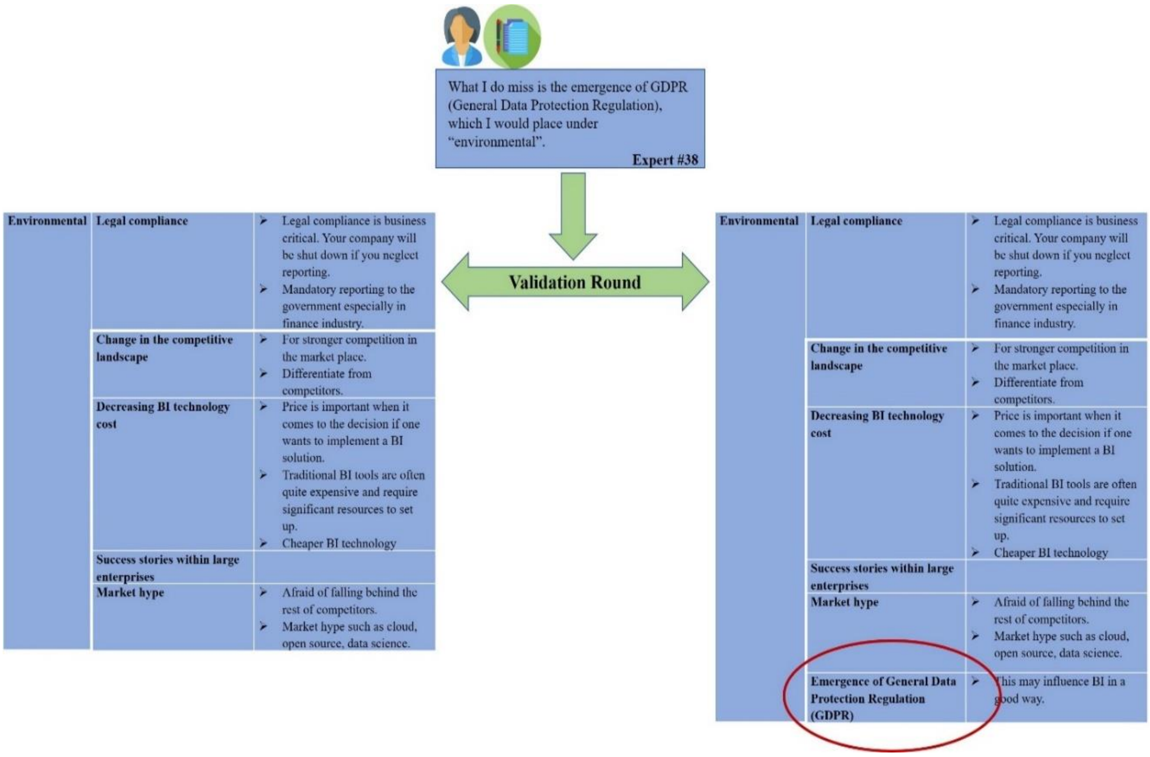

Figure 4.3: Example of analyzing the list of drivers based on the validation round

After exploring, identifying, and ranking the most important drivers and inhibitors, I conducted follow-up interviews with some BI&A experts to gain an in-depth understanding of BI&A experts considering particular items more important than others. I also examined the connections between the ranked items. As mentioned above, I utilized principles from the grounded Delphi method (Päivärinta et al., 2011). Subsequently, new core concepts emerged from the Delphi findings. The grounded approach supported theory development based on the Delphi data. The coding process revealed the interrelationships between items in the main driver and inhibitor categories (TOE). In this process, I utilized both findings from the brainstorming round and the follow-up interviews. By applying principles from axial and selective coding, five core drivers and five core inhibitors emerged (Figure 2 and 3 in Paper 5).

For the qualitative interview, expert recorded interviews and Delphi follow-up interviews were transcribed and analyzed using NVivo. Data analysis was performed using thematic analysis by Braun and Clarke (2006). The first phase was familiarization, where data was fundamentally appreciated as data and connected in different ways. In this phase, possibilities and connections between the participants, data, and existing literature were noticed. The data was read and reread. Some notes about the individual items and the whole dataset were taken. In the next phase, codes were generated to a more detailed and systematic engagement with the data. The coding phase succinctly and systematically identified the meaning through the dataset. The interesting data features were coded systematically and collated (Table 4.5). An inductive orientation of coding was performed by starting the data's analytic process, working "bottom-up" and identifying data meaning without importing ideas.

Table 4.5: Example of coding

Data	**Code**
Expert#6: So my biggest recommendation if you're thinking about the Data Lake (DL), use the DL and store the data, everything, store everything there. And you use the technologies that fit for the data you're going to store there. [….] And then you picked the data that you need from the DL and down to your Datawarehouse (DW), and then you transform your data from your DL into a structured data model and then you report them.	Data Lake as staging areas or sources for data warehouse
Expert#12: Because when you go back to this thing what comes first? [….] DW comes first and then data governance, that means when we build the DW, when we build those things we actually play as a data governance. And we started doing the job as data governance should've done but it isn't there because it wasn't established yet. Basically, what our data governance leader is doing now is to take over what we have done so far and try to structure data and do it corporate-wide and that's a huge job.	Data Governance
Expert#15: Yeah, from if we start by the lowest hanging fruit it would be automation of collecting, integrating, and making data available. Coordination production of reports, dashboards, and analysis. Provided that they already produce that stuff manually, one key value would be automating it because that's the cost-reduction. The next thing would be giving that more insight into the business.	Business value of BI&A

To continue the previous phase's active process, theme construction was performed. In this phase, similar codes are collated together with the associated data. Thus, themes are built, molded, and tested out in relation to the research questions. The next phase was revising and defining themes. This phase helped clarify the essence and scope of each theme. All coded data was compiled for each candidate theme and reviewed to ensure each theme and theme name clearly and comprehensively captured the data meaning and how it relates to the research question. The final phase produced the analysis report, presented in each publication's results section.

4.5 Validity Issues

This section discusses validity issues associated with the Delphi study and qualitative interviews.

Delphi studies have been explored in various fields, like government, medical, environmental, business, industrial, and social studies (Day and Bobeva, 2005). It is a widely accepted method for achieving a convergence of opinions concerning real-world knowledge from experts in certain topic areas (Hsu and Sandford, 2007). The Delphi group size does not depend on statistical power, but rather on group dynamics for reaching an expert consensus. There is no clear definition of an ideal panel size in the literature. Most researchers suggest a panel size between 15 and 50 participants (Kezar and Maxey, 2016). Informants are always anonymous to each other, but never to the researcher. This offered more opportunities to clarify further qualitative data. Non-response issues in the Delphi study were very low, since I obtained participation assurance.

In the narrowing-down phase, a random list of drivers and inhibitors are generated to avoid influencing informant decisions on choosing the most important drivers and inhibitors (Okoli and Pawlowski, 2004). Similarly, a randomly arranged list of drivers and inhibitors were sent to each informant in the first ranking round to eliminate bias. The questionnaires were sent to each expert in a separate email to reduce dominant individuals' influence (Dalkey, 1969). In the second ranking phase, each informant was asked to consider the average list of rankings and gave them an opportunity to change their original rankings. All informants were aware of the purpose of sharing the average item ranking, which was to gain an expert consensus (Okoli and Pawlowski, 2004). Table 4.6 demonstrates the Delphi study results' validity issues based on the criteria suggested by Day and Bobeva (2005).

Table 4.6: Validity issues of the Delphi study

Evaluation Criteria	Description
Confidence levels	• As a researcher, I acted purely as facilitator and not a participant and perform the following activities to complete the Delphi study (i.e., sending all the questionnaire to the panelists, handling and clarifying panelist's inquiry, and sending deadline reminders to the panelists. • As a researcher, I was cautious about the subjective interpretations of the consolidated list of drivers and inhibitors. Panelists were asked to validate the list during a validation phase after the brainstorming phase. The panelists were also given opportunities to write comments and justifications in the ranking and re-ranking phase when choosing the most important drivers and inhibitors, as I'm aware "failure to understand the context for the

Evaluation Criteria	Description
	consensus may lead to subsequent failure to capture important contextual information" (Day and Bobeva, 2005) p.112. • In the narrowing-down phase, the items with more than 50% of the panelist's votes were selected on the ranking phase, yielding a list of 18 drivers and 18 inhibitors. • The Kendall's W was applied as statistical analysis to measure the level of agreement among the panelists and eliminate bias (Hsu and Sandford, 2007). • The psychological factors causing random and systematic errors affecting the study are challenging to detect and acknowledge (i.e., work pressures, the time when the survey was completed, or the mood of the informant) (Day and Bobeva, 2005). This might have occurred in the validation phase, choosing the most important items, ranking and re-ranking the list.
Rigor	• The feedback from the panelists on the consolidated list of drivers and inhibitors were received, acknowledged, and reflected properly, especially feedbacks that entailed contextual changes.
Credibility	• Follow-up interviews with the informants served as a means of triangulation to provide better descriptions on the generated items. • Different perspectives have emerged among the panelists from the individual rankings and follow-up interviews, which could be attributed to the different background, experience, and job positions of each panelist.

In the qualitative interviews, informants were contacted by e-mail or phone to clarify or handle uncleared issues regarding their statements during the interview. When conducting interviews with Norwegian informants, I gave them the opportunity to do the interview in Norwegian. All my Norwegian informants were comfortable enough to express themselves in English. Thus, language barriers were not an issue in the qualitative interview or the Delphi study, since all the panelists were confident enough to complete the entire study in English language. Table 4.7 demonstrates the principles for conducting and evaluating IS interpretative research by Klein and Myers (1999) applied to assess this research.

Table 4.7: Validity issues based on the principles for IS interpretative research

Principle	Goal	Examples of how this was addressed
1. The fundamental principle of the hermeneutic circle	The iterative interpretation of the interdependent meanings of the parts and the whole they form.	By analyzing the collected data such as responses to Delphi study, informant's interviews, literature, theory, and the whole BI&A adoption phenomenon.
2. The principle of contextualization	The reflection of the social and historical background of the research setting.	By considering the informant's background and experience on the phenomenon under study and the informant's job position during the study collaboration. By including informant quotations in research publications.
3. The principle of interaction between the researchers and the subjects	The reflection on how the data were constructed through the interaction between the researcher and the informants.	By collecting informant's insights through Delphi survey, qualitative interviews, and reflections. By challenging the researcher's current understanding of the phenomena through the expert's perspectives.

Principle	Goal	Examples of how this was addressed
4. The principle of abstraction and generalization	The application of first and second principle to theoretical understanding of the phenomena under study.	By approaching the results from different theoretical lenses. Discussing the actual findings with colleagues in workshops and conferences.
5. The principle of dialogical reasoning	The sensitivity to potential contradictions between the existing theory guiding the research design and the actual findings.	By modifying coding themes based on the data generated.
6. The principle of multiple interpretations	The sensitivity to possible differences in interpretations and experiences among informants.	By considering differences in informants' perspectives with the phenomenon under study.
7. The principle of suspicion	The sensitivity to the possible biases and distortions in informant's interpretation.	By reviewing the items generated from the first Delphi questionnaire, each expert was asked to validate the list of items to ensure that all items were included and appropriately interpreted. By clarifying some uncleared issues in the qualitative data, informants were contacted through email or phone.

5 Research Publications

This chapter presents an overview of the research publications in the thesis. The list of publications is presented in Table 5.1. The full text versions of these articles can be found in Appendix B.

Table 5.1: Overview of research publications

No.	Publication	Publication Outlet
1	Llave, M. R. (2019) A Review of Business Intelligence and Analytics in Small and Medium-sized Enterprises.	Accepted to the International Journal of Business Intelligence Research (IJBIR).
2	Llave, M. R., Hustad, E., & Olsen, D. H. (2018). Creating Value from Business Intelligence and Analytics in SMEs: Insights from Experts.	Proceedings of the 24th Americas Conference on Information Systems (AMCIS), New Orleans, Louisiana, USA.
3	Llave, M. R. & Olsen, D. H. (2018). Drivers of Business Intelligence-Based Value Creation: The Expert's View	Proceedings of the 12th Mediterranean Conference on Information Systems (MCIS), Corfu, Greece.
4	Llave, M. R. (2018) Data Lakes in Business Intelligence: Reporting from the Trenches.	Proceedings of the 10th International Conference on Enterprise Information Systems (CENTERIS), Lisbon, Portugal.
5	Llave, M. R., Hustad, E., & Olsen, D. H. Creating strategic business value from BI&A: Navigating the dire straits between investment and performance	Under Review – Journal of Strategic Information Systems

5.1 Paper 1: A Review of Business Intelligence and Analytics in Small and Medium-Sized Enterprises

When embarking on a research endeavor, a literature review is vital to evaluate prior research and identify significant studies within the interest domain. The goal is to provide a comprehensive review of BI&A literature in the SME milieu. The review was carried out and focused on these following research questions:

(1) What research topics of BI&A in SMEs have been addressed in previous research?
(2) What are the pertinent research topics on BI&A in SMEs that should be addressed in the future?

There is currently no comprehensive review and assessment of this research domain. I believe this literature review elicits more insights contributing to understanding in this domain and inspiring future related research.

5.1.1 Presentation

The first article applied a comprehensive and systematic method for review by Kitchenham (2004). This literature review covered articles published between 2000 and 2018. A total of 78 articles were identified and reviewed. To present the study's findings, these articles were categorized using the concept-centric method by Webster and Watson (2002). The distribution of publication source, publication year, citation status, and research method of the included articles were depicted. This review summarized existing research topics, identified research gaps, and presented future research suggestions.

5.1.2 Findings

The review identified several research gaps. The subsequent paragraphs provide a brief discussion of those gaps related to my research work.

First, it is crucial to have a detailed understanding of BI&A components to achieve a solid architecture design and BI&A successful implementation. However, there is a lack of focus on understanding BI&A components and their importance when embarking on a BI&A project. There are studies addressing BI&A components (Gupta and George, 2016, Mikalef et al., 2017), but they did not report on SME specific context. Therefore, more studies exploring the purpose of BI&A components in assessing SME readiness for BI&A initiatives are needed.

Second, most extant literature pertains to traditional manufacturing SMEs employing BI&A. Hence, there is a lack of research on different industry types applying BI&A. These studies may result in different research findings and help make BI&A more mainstream in SMEs. Therefore, more research is needed on various industry types employing BI&A to their business.

Third, there is a lack of research on different technologies and techniques to extend the capabilities of traditional BI&A. For instance, expanding the selection of BI&A initiatives like implementing BI&A with or without data warehouses, applying the automated data warehouse approach, and machine learning techniques. Therefore, these issues need further investigation.

Lastly, capturing BI&A business value can offer different perspectives. It requires SMEs to go beyond technical implementation. However, few studies evaluate BI&A benefits. Even though the importance of understanding the different mechanisms and processes for creating BI&A business value has been emphasized in the literature (Mikalef et al., 2017), there is a lack of studies to improve BI&A business value understanding and how these systems can help create intelligence. It is crucial to investigate how BI&A creates business value and how the factors affect value creation.

5.2 Paper 2: Creating Value from Business Intelligence and Analytics in SMEs: Insights from Experts

This second article is based on an exploratory study with BI&A experts. In this study, how BI&A enables information usage and how it turns data into usable information are important (Larson and Chang, 2016). Since SMEs differ from large enterprises in many ways, it is crucial to understand how SMEs transform data into meaningful information from using BI&A. We investigated these issues by addressing this research question: *How are SMEs creating value from BI&A systems?*

5.2.1 Presentation

The goal of this paper is to investigate the implementation, utilization, and value creation of BI&A. By performing an exploratory study, 24 interviews were conducted with experts from user organizations and vendors in different industries. Data analysis concentrated on issues affecting how SMEs implement, utilize, and create value from their BI&A investments. This study adapted a value framework by Trieu (2017), combining several known frameworks from IS literature that utilizes a process theory approach (Soh and Markus, 1995, Melville et al., 2004, Schryen, 2013) to understand the BI&A processes of value creation in an SME. These consist of BI&A conversion process, BI&A use process, and competitive process used to organize and present the study results.

5.2.2 Findings

The data analysis recognized several critical issues highlighted by the informants observed in SMEs: “start small, think big” strategy, BI&A investment without a traditional data warehouse, BI&A with automated data warehouse approach, and data governance. These are BI&A investment issues under the BI&A conversion process.

First, “start small, think big” is considered an appropriate BI&A investment strategy for SMEs. Since most SMEs have limited resources, an iterative and gradual investment strategy will help SMEs obtain value in quick wins. Most informants explained when the BI&A investment delivers value into the organization, it will be easier to continue the project. Several informants pointed out the importance of BI&A being dynamic and agile to evolve over time.

Second, traditional data warehouses are complex and costly for SMEs. Typically, SMEs have no real need and no budget to embark on this project. Most informants stressed the importance of immediate data access for analysis than having all the data in one place. Therefore, they considered BI&A without building a traditional data warehouse as an appropriate solution for SMEs. This topic is not covered in extant literature, making more studies on this issue necessary.

Third, the automated data warehouse is another means to avoid the traditional data warehouse project. This approach is faster and cheaper than the traditional data warehouse. It is also considered a feasible solution for SMEs. However, there is no empirical study on an automated data warehouse approach. This issue should be further investigated.

Another issue influencing the BI&A conversion process is data governance. Many informants explain data governance means having control of data availability, usability, integrity, and security. Therefore, informants noted implementing data governance framework is not easy. In the BI&A use process, several informants pointed out the contextual difference of BI&A usage in various industries. They also perceived several significant BI&A benefits, including business insight, customer insight, cost reduction, and competitive advantage. Further, the competitive process received the least attention from the three BI&A processes. Most informants acknowledged its importance on BI&A value creation.

5.3 Paper 3: Drivers for Business Value Creation of Business Intelligence: The Expert's View

Article 3 focused on BI&A business value creation. However, despite the popularity of business value in IS research (Schryen, 2013), little empirical research has addressed BI&A business value (Elbashir et al., 2013). It is crucial to learn more about the value creation processes induced by BI&A. Against this backdrop, this study seeks to answer the following research question: *What are the factors influencing the BI&A business value creation process?*

5.3.1 Presentation

Assessing BI&A success is usually problematic since most of its benefits are long-term, indirect, and difficult to measure (Seddon et al., 2010). This paper investigated factors influencing BI&A-based value creation. Through an exploratory study, 16 semi-structured interviews with experts from different industries were conducted. Data analysis concentrated on identifying *implementation drivers* of BI&A-based value creation and BI&A business value. As an underlying framework, this study utilized the same framework by Trieu (2017) to illustrate the BI&A-derived value creation.

5.3.2 Findings

The thematic analysis showed the informants highlighted some factors affecting the BI&A business value creation process. The analysis recognized four significant implementation drivers of BI&A-based value creation: business case, BI&A strategy, data governance, and organizational adaptability. The main reason why business case affects the BI&A conversion and use process is because building a business case for SMEs helps demonstrate how BI&A is worth the investment. According to most informants, to include business case as part of the business strategy can ensure that the BI&A investment will support the strategic objectives of an organization.

BI&A strategy influences the entire BI&A value creation process. Several informants argued formulating a strategy provides a goal and direction to any project. The literature shows the importance of identifying the business reasons for an investment, strategic goals, and the application goals for any planned solutions (Hočevar and Jaklič, 2010). Hence, enterprises should formulate business and IT objectives to derive value from BI&A (Williams and Williams, 2010).

BI&A investment can be very expensive when the information it provides is not accurate or does not comply with the enterprises' information needs (Hočevar and Jaklič, 2010). Data governance maintains the reliability, validity, integrity, and accountability of data to help improve data quality. In concert with organizational adaptability, the organizational change is vital to leveraging the full potential of BI&A (Hribar Rajterič, 2010). It influences the attitude of an organization to BI&A use (BI&A use process). According to the literature, there is a positive relationship between information quality and information use (Petter et al., 2008, Citroen, 2011). Also, information quality and information use are two dimensions for successful value creation. Data governance affects the BI&A conversion process and organizational adaptability affects the BI&A use process.

This study also documents the main BI&A business value, including automation, business insight, and decision support. By identifying these four drivers and presenting business value obtained from BI&A systems, this study contributed to improving understanding of BI&A-based value creation.

5.4 Paper 4: Data Lakes in Business Intelligence: Reporting from the Trenches

The fourth article is based on an exploratory study with BI&A experts, it examines the capabilities of data lake in enterprises. Article 4 further investigates this topic by these research questions:

(1) What are the purposes of implementing data lake into BI&A architecture?
(2) How do data lakes affect the BI&A architecture of an enterprise?
(3) What are the benefits and challenges of implementing data lake into BI&A architecture?

5.4.1 Presentation

Due to unprecedented volumes and accumulations of data known as big data, BI&A face new challenges and exciting opportunities (Ram et al., 2016). Big data has led to the emergence of modern technologies like data lake and made it possible to acquire a large amount and variety of data (Larson and Chang, 2016). Data is needed to support decision-making on every level. Since data is the underlying source of BI&A, it is crucial to understand how data lake technologies influence BI&A.

Article 4's purpose was to explore data lake's role in BI&A architecture and to find out how enterprises use data lakes. To do so, 12 semi-structured interviews were conducted with experts who have hands-on experience with BI&A and data lake technologies. The data analysis resulted in perceived benefits, purposes, and challenges of data lake technologies.

5.4.2 Findings

This paper provided the results of an exploratory study designed to understand how data lake technologies are used in practice by enterprises. The analysis discovered three purposes of data lake technologies highlighted by the informants: as staging areas or sources for data warehouses, as a platform for experimentation for data scientists and analysts, and as direct sources for self-service BI&A. During the interviews, most informants mentioned the importance of utilizing data lakes as a staging area for data warehouses to handle any type of data. For example, data from sensors, clickstreams, and web logs which relational databases like SQL cannot handle. Most informants considered data lake a useful component in BI&A architecture and an extension of BI&A concept.

According to many informants, data scientists and analysts are the power users of data lake technologies. Data lakes give these power users the ability to easily configure and reconfigure their models or queries on the fly. Hence, data lakes are the experimentation platform for them. Another purpose of data lake is a direct source for self-service BI&A. Many informants stated data lakes are used to provide data for BI&A reporting and analytical tools. However, there was no information explicitly discussing this issue, which needs further investigation.

The study also identified some perceived benefits of data lake technology. These benefits are mainly related to storing, acquiring, handling, and preserving the data. The informants also revealed several challenges of data lakes based on experience, requiring further investigation.

5.5 Paper 5: Creating Strategic Business Value from BI&A: Navigating the Dire Straits between Investment and Performance

Since BI&A has become an increasingly important information technology investment in enterprises and SMEs constitute over 99% of enterprises in world economies, research on BI&A in SMEs is considered vital. This study applied the Delphi method over four stages with 39 BI&A experts to answer the following research questions:

(1) What are the drivers for BI&A adoption in SMEs?
(2) What are the inhibitors for BI&A adoption in SMEs?
(3) Why are these drivers and inhibitors important for BI&A adoption in SMEs?

5.5.1 Presentation

BI&A systems are now used extensively in many areas of decision-making to create business value (Trieu, 2017). However, research on BI&A in SMEs are not fully investigated. The purpose of the fifth article was to identify the crucial factors affecting BI&A adoption and further understand the process of SME BI&A adoption. The data were collected from 39 experts from various industries using a ranking-type Delphi study with a grounded Delphi approach followed by qualitative interviews. The data analysis resulted in five core drivers and five core inhibitors.

5.5.2 Findings

This paper offered some important insights into BI&A adoption in SMEs through a Delphi study. This study identified 18 drivers and 18 inhibitors which were categorized into five core drivers: (1) need for better data management, (2) need for better information and reporting, (3) desire for better business operations, (4) desire to improve business value, and (5) need to follow legal requirements; and five core inhibitors: (1) challenging organizational data environment, (2) BI&A

project challenges, (3) low organizational readiness, (4) low organizational change capability, and (5) BI&A market challenges.

These core drivers and inhibitors were mapped onto Soh and Markus' IS value process model to better understand BI&A value creation. This paper's findings demonstrate low organizational readiness as the most important core inhibitor and indicate resource poverty is the main reason. Therefore, a set of recommendations was proposed to improve organizational readiness in SMEs. Moreover, the follow-up interviews with several experts emphasized an iterative and gradual process of BI&A investment. Many experts used the expression "start small, think big" to denote this strategy. Several experts emphasized BI&A should evolve over time, having an iterative development will support further BI&A system development. This approach will contribute to building the legitimacy of further BI&A investments and making BI&A effort business-driven. The overall paper results offer a better understanding of BI&A adoption and SME value creation.

6 Contributions

This study is entailed to generate a better understanding of SME BI&A adoption. To do so, the following research question has guided this doctoral research: *How can we understand the phenomenon of BI&A adoption in SMEs?* To answer this research question, a Delphi study and qualitative interviews with BI&A experts were conducted. This research was designed to provide a better understanding and explanation of SME BI&A adoption, and how BI&A initiatives generate value when implemented and used. The research endeavor resulted in five research articles (Chapter 5). I answered the main research question by providing five main contributions: (1) it provides an overview of BI&A adoption in SMEs by synthesizing extant research contributions on this topic, (2) it contributes to the body of research focusing on BI&A adoption in SMEs and has identified key BI&A drivers and inhibitors to explain adoption and reluctance to adoption (non-adoption), (3) it contributes to the understanding of how SMEs can utilize BI&A initiatives to generate investment value, (4) the thesis suggests a revised (adapted) value model allows for more dynamics, agility, and iterations in its stages better fitting SME, and (5) the thesis explains its findings on BI&A adoption in SMEs based on the integration of three theoretical perspectives which provides explanatory strength; the resource-based view of the firm, dynamic capabilities, and an IS value model perspective. Furthermore, the thesis makes certain implications for practice including a set of recommendations for how SMEs should design and implement the BI&A business case. I elaborate on these contributions for research and practice. Finally, the combination of research methods applied in this study can be seen as a methodological contribution.

6.1 Contribution to Research

First, I conducted a literature review on BI&A adoption in SMEs to understand and synthesize extant research contributions on this topic. Based on the research gaps identified, I define my study's scope (Paper 1). This study provides an overview of SME BI&A adoption, which is valuable for the IS research community.

Second, the main contribution of the study is the identification of the core drivers and inhibitors of BI&A adoption in SMEs (Paper 5). By using Soh and Markus's

IS value process model, this study illustrates how the identified core drivers and inhibitors influence the BI&A adoption and value creation process (Figure 6.1).

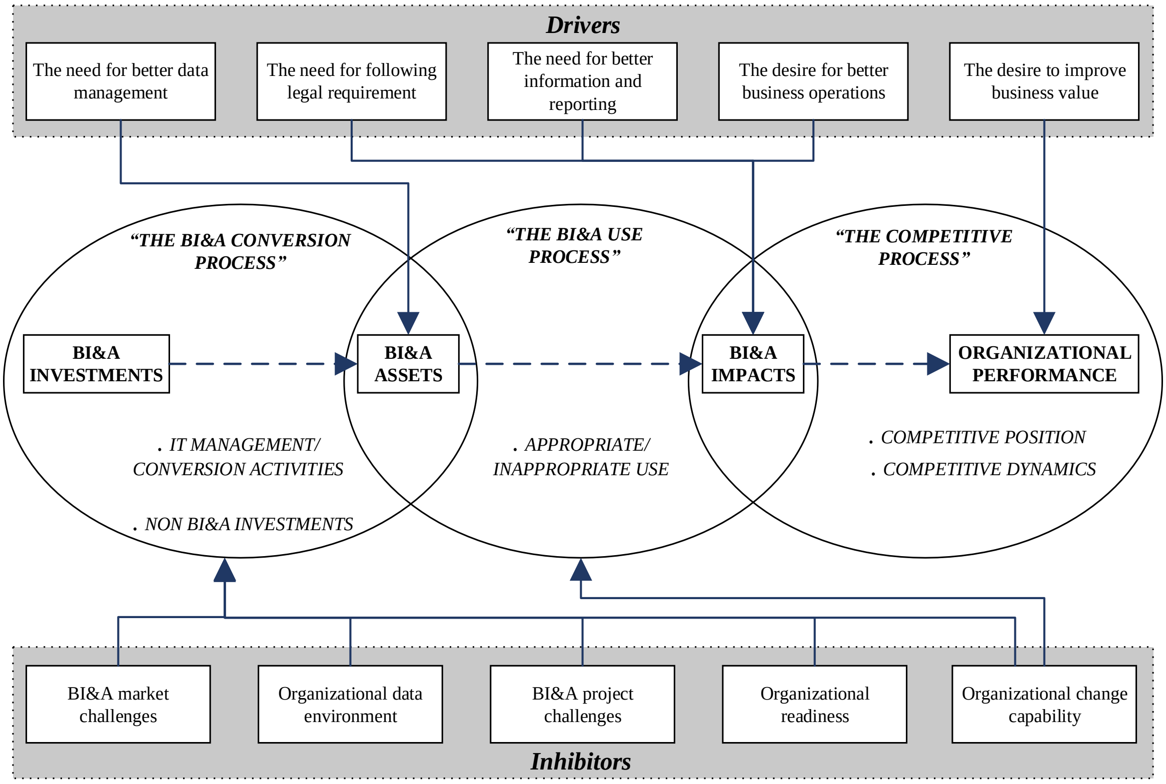

Figure 6.1: Core drivers and inhibitors for BI&A adoption in SMEs mapped onto the IS value process model (Soh and Markus, 1995)

Comparing the first core driver category, the desire to improve business value, to Soh and Markus' definitions, I found this category relates to the organizational performance construct. This core driver contains four items, the desire to improve enterprise performance, the need to increase competitive advantage, the desire to increase profitability, and BI&A is an executive priority. When BI&A is an executive priority, it is more likely they are willing to use BI&A for decision-making and they have knowledge of BI&A business value. I therefore conjectured this core driver will result in organizational performance. The three next core driver categories related to BI&A impacts include better ability to follow legal requirements, the need for better information and reporting, and the desire for better business operations. BI&A impacts can be improved products and services, improved operational efficiency or processes, and strengthened organizational intelligence. I believe these impacts can be attained by SMEs through the three core drivers. They therefore relate to the BI&A impact construct. The last category of drivers, the need for better data management, is clearly related to the need for

BI&A assets. In decision-making, quality information is important for taking quality decision (Ali et al., 2018). When BI&A becomes a vital resource for quality information, organizations will consider BI&A as a reliable aid for decision-making. In addition, the selection and adoption of BI&A assets depends on its data environment (Trieu, 2017). Therefore, the need for data management relates to BI&A asset construct.

The study also found the lack of resources is an important factor for explaining slow adoption and non-adoption of BI&A in SMEs. SMEs suffer from resource poverty like lack of staff, expertise, time, and financial resources. The study further documents SMEs lack understanding about BI&A, lack BI&A readiness, and are unable to realize value from BI&A. The lack of resources pertains to both physical and human assets. Physical assets are infrastructure shared across the organization and business applications utilizing infrastructure (Fink et al., 2017). Human assets include the knowledge and skills possessed by human resources or the BI&A team. BI&A assets contain the combination of infrastructural technologies and tools to create a technological environment enabling organizations to create BI&A capabilities. The BI&A team are human resources responsible for leading organizational BI&A initiatives. I conjectured SMEs' lack of resources results in low organizational readiness for BI&A adoption. Thus, it explains why SMEs remain reluctant to adopt BI&A. This result was consistent with Gibson and Arnott (2003), who proposed a lack of resources is a challenge for BI&A adoption in SMEs. This thesis confirms a lack of resources is a critical issue in BI&A adoption in SMEs.

The importance of organizational readiness has been reported in IS adoption (Raymond and Uwizeyemungu, 2007, Sammon and Adam, 2010) and BI&A adoption literature (Williams and Williams, 2010, Anjariny and Zeki, 2014, Puklavec et al., 2014, Hidayanto et al., 2012). However, literature on organizational readiness is not specifically focused on the SME context. Hidayanto et al. (2012) had a specific focus on measuring organizational readiness in SMEs. However, factors they identified for their measurements are generic and not particularly SME specific. In addition, Puklavec et al. (2014) also identified organizational readiness as an important factor for BI&A adoption in SMEs without explaining the meaning of it. The results of this thesis are SME specific. BI&A experts from the Delphi study provide suggestions to include in the organizational readiness construct. I found the lack of BI&A skills, limited resources, lack of BI&A awareness, and lack of analytical culture are crucial inhibitors of organizational readiness (Figure 3 in Paper 5). I conjectured this thesis offered a deeper understanding of organizational readiness for BI&A adoption in SMEs.

This study also investigated how BI&A is implemented in the SME context. The results show SMEs' lack of resources influences BI&A implementation projects. This study illustrates how SMEs can invest in cheaper and faster BI&A assets. BI&A is no longer reserved for enterprises with massive resources. Some SMEs have invested in cheaper and faster BI&A solutions to avoid the traditional BI&A, which are costly, resource-intensive, and complex undertaking. By exploring BI&A adoption in SMEs, the study contributes to the SME BI&A system implementation research stream. The study findings introduced cheaper investments for SMEs, like BI&A without a data warehouse and BI&A with an automated data warehouse. I believe other types of BI&A investments are cheaper and faster to introduce to SMEs than traditional BI&A investments (Paper 2).

Third, this study demonstrates how SMEs can utilize and generate BI&A business value. The results show most SMEs utilized BI&A for automated reporting and simple analytics enabling informed decision-making. BI&A provides SME business insights, for instance, the cost of acquiring new customers over time and how those costs are related to customer gain or loss. It also provides information for SMEs to make better informed decisions in staffing, ensuring correct pricing, and planning production. Most experts pointed out banks and insurance are the early adopters of BI&A. However, study findings indicate other industries like production, manufacturing, architectural, and equity industries can utilize and generate value from BI&A investments. The study also illustrates BI&A adoption is considered successful when SMEs are continuously obtaining business value from BI&A. I conjectured perceptions of potential business value are important for successful BI&A adoption. Gibson and Arnott (2003) suggested knowledge of BI&A business value as an important factor affecting BI&A adoption. However, their findings lack empirical evidence. This thesis provides an empirical ground to show its importance. The different business values of BI&A are particularly discussed in this thesis (Papers 2 and 3).

Fourth, this study's results demonstrate an iterative and gradual approach is preferable for SMEs (Papers 2 and 5). This iterative approach works according to the "start small, think big" investment strategy, where huge tasks in BI&A projects will be broken down into smaller and more manageable parts called iterations. I argued SMEs will not realize the importance of BI&A investment before going through many iterations. Through iterations, it is critical to focus on things which are easy to deliver and give value to the business. Most experts stated it is better to do small deliveries to prove the concept with a series of quick, high-profile wins to demonstrate the value and gain executive trust while gradually building out the long-term vision of BI&A. By realizing quick wins, it would be easier for SMEs to get resource commitment for further investments. This study shows the importance of the iterative strategy, contributing to building the commitment and legitimacy of further BI&A investments. One study in the literature touched on this issue (Yeoh and Koronios, 2010). They investigated how BI&A technology should be implemented. Their study's findings show a BI&A system evolves through an iterative process of development in accordance with dynamic business requirements. I confirmed the importance of an iterative approach in BI&A adoption in SME. I argued combining findings from Yeoh and Koronios (2010) with my results yield better empirical evidence on the importance of iterative approach in BI&A.

BI&A is a constantly evolving strategy, vision, and architecture that should continuously align with the organization's operations and direction with its strategic business goals. BI&A should be dynamic and evolve over time. The Soh and Markus' IS value process model fails to illustrate BI&A's dynamic nature. This study suggests a revised value process model to represent the iterative and dynamic nature of BI&A. Figure 6.2 depicts how the value process model has been revised with feedback loops (Paper 2). Consequently, the study also identifies four implementation drivers influencing BI&A value creation. These drivers are mapped onto the IS value process model to show how each driver can affect the BI&A value creation process (Figure 6.2). Data governance can influence the BI&A conversion process. In decision-making, the quality of information is evident for quality decisions (Ali et al., 2018). I argued the role of data governance can improve the BI&A conversion process by assuring BI&A assets can be a reliable resource for quality information. Soh and Markus (1995) stated quality BI&A assets, if used effectively, may yield desired BI&A impacts and further yield organizational performance. Data governance can help SMEs ensure their BI&A investments will result in quality assets for organizations to use (Paper 2 and 3).

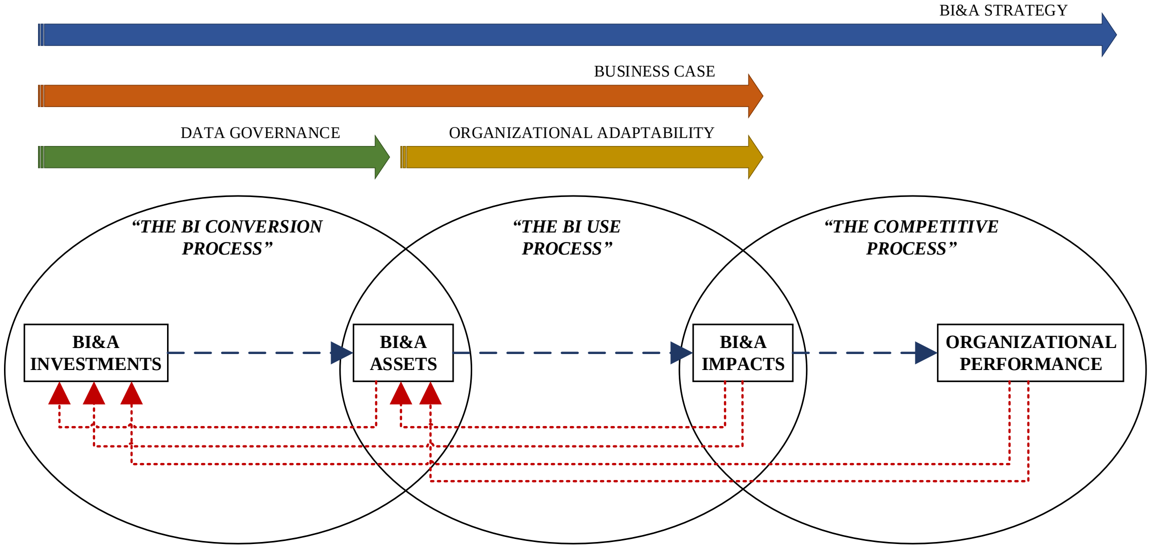

Figure 6.2: The proposed revised value process model and implementation drivers mapped onto the IS value process model by Soh and Markus (1995)

Lastly, the study utilized three theoretical perspectives to better understand the study's results: RBV theory, dynamic capabilities, and IS value process model. This study utilized RBV theory to provide a theoretical lens for understanding the role of SME resources in BI&A adoption. RBV is an appropriate lens to see how a firm's resources are a potential source of competitive advantage, which may result in improved organizational performance in BI&A adoption. I argued resources are important to gain the ability to adopt and create value from BI&A initiatives.

The RBV argues when firm resources are economically valuable, relatively rare, difficult to imitate, and non-substitutable (VRIN) can result in a sustainable competitive advantage (Wade and Hulland, 2004). However, neither IT assets nor organizational resources satisfy this VRIN criteria. The VRIN criteria are based on how resources are accessed, combined, and deployed to generate competitive advantage (Grant, 1991, Moran and Ghoshal, 1999). I argued even though BI&A technologies are considered a commodity software, the ways an organization assimilates BI&A in its business process are unique. The same as the policies and business rules governing the organization's business practice. Once a BI&A solution becomes the norm, it is likely to become entrenched in a business for a long time. I contended BI&A can become a VRIN resource over time, especially when SMEs become more mature in BI&A adoption. Through iterations, SMEs will gradually develop the ability to adapt to change and implement BI&A, which eventually become VRIN resources.

When an SME can continually modify BI&A assets and manage to update the BI&A capability, it can be a source of dynamic capabilities. Reconfiguring and renewing resources into new organizational capabilities through sensing, seizing, and transforming to address the rapidly changing environment are the focus of dynamic capabilities (Teece et al., 1997). The RBV theory conceptualized organizational resources as static, neglecting changes due to the turbulent environment. Dynamic capabilities were conceptualized in response to this criticism. Most businesses change quite frequently. New products and services are created, new data sources become available, resulting in new systems needing to be interfaced, like application in the Cloud. I argued SMEs possess dynamic capabilities when their BI&A assets are flexible enough to adapt to a fast and frequently changing environment. Through dynamic capabilities, SMEs can sense, seize, and transform when changes occur in the environment and create resource configuration to provide a sustainable competitive advantage. I find an iterative strategy where SMEs can gradually and continually renew their BI&A investments, can promote dynamic capabilities' development, which can become a valuable competitive driver for SME BI&A adoption.

I also argued the IS value process model by Soh and Markus is the most appropriate to understand BI&A adoption in SMEs. Other IS adoption models like TAM, UTAUT, and D&M's IS success model are widely used to investigate individual users' adoption of IS/IT, like BI&A (Ain et al., 2019). I argued these adoption models only provide a simple view of BI&A adoption. In contrast, the study's findings demonstrate adoption issues at the organizational level are significant. I believe analysis at the organizational level would be most appropriate for BI&A adoption research. Recent studies have utilized DOI theory as an analytical lens to explain BI&A adoption in SMEs. The focus on iterative stages and organizational value also renders DOI theory an inappropriate lens to understand adoption. The DOI theory misses the iterative nature of BI&A projects. This study shows BI&A should be a long-term iterative project and not a set of stage-gate (waterfall) styles of adoption. Another shortcoming of DOI is it also misses the significance of the adoption performance stage. The confirmation stage is one stage in the five-stage version of DOI, where the individual or the organization finalized the decision to continue using IS/IT. I argued the performance stage does not just confirm the technology works. DOI should be amended with performance stage and iterations between stages to account for the iterative building of organizational acceptance and resource allocations.

The BI&A value process model illustrates BI&A value creation process as a set of sequential stages, where each is completed before progressing to the next stage. Successful BI&A initiatives with sustaining business value are not completed in a “one and done” project. When BI&A is successful in an organization, it will continually expand with new data, technologies, analytics, and business uses will become apparent. The findings demonstrate the revised process model is appropriate to understand BI&A adoption value in SMEs. Many IS researchers adopted these three theoretical perspectives. Previous literature reported using two of these theoretical perspectives. For instance, Olszak (2016) applied a combination of the RBV theory and the dynamic capabilities to investigate BI&A failures. Likewise, Božič and Dimovski (2019b) applied both the IS value process model and the dynamic capabilities perspective to explain how BI&A use is associated with innovation ambidexterity and firm performance. They focused on the BI&A use process and the competitive process, but not the adoption and value creation process. These theoretical perspectives are considered solid theoretical foundations for BI&A literature and offer a better understanding of the thesis results.

6.2 Contribution to Practice

The findings of this study provide a foundation for making practice recommendations. I first highlighted the importance of evaluating BI&A investments based on the available resources and the SMEs’ financial situation when embarking on a BI&A project. BI&A projects introduce different technologies and products into an organization, like reporting tools, data integration tools, and database platforms. The costs of these technologies range from free to very expensive. In addition to the cost of acquiring the right software and technology for BI&A investment, the total cost of deploying BI&A is a primary SME concern. Since the lack of resources is an important factor in BI&A

adoption and non-adoption, it is vital to define requirements based on available resources. It is important to document the list of requirements and expectations to create the foundation of a successful BI&A. Both BI&A vendors and SMEs should pay attention to this process. I contended the importance of evaluating BI&A investments based on available resources and the financial situation of SMEs when embarking on a BI&A project.

Second, the empirical findings obtained using expert interviews and a Delphi survey show the “start small, think big” or iterative strategy is an appropriate investment approach for SMEs. BI&A should be built incrementally and iteratively. Typical SMEs have zero exposure to advanced analytics. Most experts implied an iterative approach means starting with the “low-hanging fruits” of BI&A like automated reporting, dashboards, and simple analytics SMEs can exploit. This can be achieved by addressing simple use cases first and realizing value before iteratively adding extensive functionality. SMEs with few data sources adopt BI&A assets that are pre-built solutions like PowerBI, Tableau, and QlikView without building data warehouses. When the goal is to improve reporting and apply simple analytics on top of their BI&A environment, it is feasible to skip the data warehouse part of a BI&A investment. When the goal is to have an enterprise-wide definition of the data and the data environment is more complex, BI&A with automated data warehouse could be a feasible option for SMEs (Paper 2). These findings are valuable for SMEs, vendors, and consultants.

This study illustrates the importance of building a business case when embarking on a BI&A project. By building business case, SMEs can demarcate and identify specific types of problems affecting the profitability and efficiency of an organization, also known as “business pain.” The business case will also include the type of BI&A investments and discuss how this investment can reduce business pain. It will help SMEs see the balance between the costs involved and the business value gained from this technology. More importantly, this thesis demonstrates a business case should be a part of the business strategy and have a clearly defined purpose to ensure it will support the business objectives. This is consistent with Yeoh and Koronios (2010), illustrating the need for a strong link between business objectives and BI&A projects to contribute to a successful BI&A. Other scholars recognized the importance of a well-established business case (Hidayanto et al., 2012, Anjariny and Zeki, 2014), however, any suggestions on achieving this are not fully addressed in literature. This thesis contributed to this and confirmed the importance of the business case with empirical evidence (Paper 3).

Fourth, the study's findings also confirmed the importance of data governance. This study demonstrated how earlier BI&A investments failed due to data quality issues. These issues are not apparent until business users test BI&A solutions just before going "live." According to the study's results, both SMEs and large enterprises must recognize data as an enterprise asset. As demonstrated in the literature, it is crucial to consider the data quality in organizations to ensure successful BI&A adoption (Anjariny and Zeki, 2014, Olszak and Ziemba, 2012). Data governance can help maintain the accuracy, consistency, accessibility, integrity, and security of information across organizations. In addition, it also helps with data creation and data consumption. Thus, establishing a data governance program to solve data quality issues and help organizations treat their data as a corporate asset. I contended the importance of data governance in BI&A value creation and adoption in SMEs (Papers 2 and 3). Moreover, it is critical to mention business people, not IT people, should be the key driver in data governance efforts. People from business should create data definitions, business rules, and KPIs for their data governance program.

Finally, this thesis' findings also suggest implementing a cost-effective technology. This study recommended implementing data lake technology as part of the low-cost BI&A environment for SMEs. The data lake concept popped up with big data's advent and became a part of BI&A technology. BI&A focuses on transforming raw data into usable, valuable, and actionable information to improve decision-making. With the advent of big data, the concept, architecture, and capabilities of BI&A will change. In this thesis, data lake technology was implemented to provide an agile and affordable environment for SMEs to store and analyze data. SMEs implemented the data lake to act as the main repository for all data. This means the data lake serves as a staging environment for SMEs storing all data without building and designing a data warehouse. SMEs can have all the data at their disposal for both reporting and analysis to provide a self-service BI&A. Implementing data lake technology can be argued as part of the iterative approach or "start small, think big" strategy where incremental steps achieve the BI&A environment SMEs demand. Having data lake technology as part of the BI&A environment is an example of BI&A without data warehouse investment and offers an understanding of why an iterative approach is preferable for SMEs. The expert interviews illustrate the data lake as an important trend to help BI&A become more mainstream in SMEs.

SMEs and large enterprises implemented data lake technology to complement the limitations of traditional data management tools and serve as an experimentation platform for data scientists and analysts. It is crucial to mention even though the data lake offers the functionality of a traditional data warehouse but without the upfront development cost (ETL), the data lake technology does not replace the data warehouse architecture. Other related issues, like the purposes, benefits, and challenges of data lake technology were also presented in this thesis (Paper 4). This study further shows both SMEs and large enterprises can adopt data lake technology as part of the BI&A environment. Table 6.1 provides an overview of this chapter's recommendations.

Table 6.1: Recommendations to practice

Recommendation	Description
1. Perform a BI&A investment evaluation	Evaluate BI&A investments based on the resources available and the financial situation of the SMEs.
2. Start small, think big strategy	Build BI&A incrementally and iteratively. By addressing simple use cases first and realizing the value before iteratively adding more extensive functionality. This means starting with the "low-hanging fruits" of BI&A such as automated reporting, dashboards, and simple analytics which SMEs can exploit.
3. Build a business case	Build a business case by demarcating specific types of problems affecting the profitability or efficiency of an organization also known as "business pain". To examine what type of BI&A investments and how this investment will reduce the business pain of an SME. This will help SMEs to see the balance between the costs involved and the business value gained from BI&A.
4. Implement data governance	Establish data governance to help maintain the accuracy, consistency, accessibility, integrity, and security of information across the organizations. It is important to help manage both the data creation and data consumption. A data governance approach will help organizations to treat its data as a corporate asset and maximize its value.
5. Implement a cost-effective technology	Implement cost-effective technologies like data lake to provide an agile and affordable BI&A environment for SMEs. To complement the limitations of the traditional data management tools.

6.3 Methodological Contribution

My research approach has been to focus on a better understanding of SME BI&A adoption. To reach this goal, I applied an exploratory approach with two different research methods. First, I conducted a ranking-type Delphi study with a grounded Delphi approach to identify, map, and prioritize the themes of specific topics gathered from the Delphi survey. I found this combination appropriate to provide a richer understanding of the investigated topic by identifying core themes and their interrelationships. Second, I conducted an exploratory qualitative study using the expert interview technique to explore the investment, implementation, utilization, and value creation of BI&A. The extant BI&A literature is dominated by quantitative methods (Ain et al., 2019). By utilizing an exploratory approach, I was able to achieve a more comprehensive picture of the factors influencing BI&A adoption in SMEs. However, this would not have been possible with applying quantitative methods. Therefore, I contended the research approach applied in this study provides a deep and better understanding of BI&A adoption in SMEs.

7 Conclusions

This thesis is one of a few studies investigating and exploring SME BI&A adoption. This chapter summarizes the thesis' findings. I will also discuss the thesis' limitations and make future research suggestions.

7.1 Summary

This thesis explores the investment, implementation, utilization, and value creation of BI&A and contributes to our understanding of the phenomenon of BI&A adoption in SMEs. The main research question focused on obtaining a better understanding of the phenomenon of BI&A adoption in the SME context: "*How can we understand the phenomenon of BI&A adoption in SMEs?"* To address this research question, I first reviewed the literature on BI&A adoption in SMEs to understand the extant research contributions on this topic and define my study's scope.

The main research question was addressed by conducting a Delphi study and an exploratory study of qualitative expert interviews. Three theoretical perspectives (RBV theory, dynamic capabilities, and IS value process model) have informed the research findings' interpretation. I identified and explored the core drivers and inhibitors influencing BI&A adoption and value creation. The following research sub-question addressed these topics. *SQ1: "What are the drivers and inhibitors of BI&A adoption in SMEs?"* The core drivers and inhibitors were identified through Delphi rankings and interviews. These core drivers and inhibitors were identified by the expert focus primarily on adoption issues at organizational level. The identified core drivers and inhibitors were mapped onto Soh and Markus' value process model to show how each factor affected BI&A value creation. SMEs' lack of resources, resulting in low organizational readiness, is the most important factor for the slow adoption and non-adoption of BI&A (Paper 5).

This study also addressed two more research sub-questions: *SQ2: "How are BI&A utilized and implemented in SMEs?"* and *SQ3: "How do SMEs create value from BI&A initiatives?"* Since the lack of resources was an important factor for slow adoption or non-adoption of BI&A, this study shows the importance of approaching BI&A investments iteratively. The iterative and gradual approach of investing and building BI&A assets was preferable for SMEs. The "start small think big" strategy was emphasized in both the Delphi study and the exploratory interviews. This thesis shows the importance of an iterative approach on successful BI&A value creation. I propose a revised value process model to represent the iterative and dynamic nature of BI&A (Paper 2).

This thesis also identifies four *implementation drivers* mapped onto the IS value process model to show how it influences BI&A value creation (Paper 3). Among these drivers, data governance and building a business case are the most significant and were considered relevant implications for practice. BI&A utilization among various SMEs and the business value generated from BI&A investments are also presented in this thesis (Paper 2 and Paper 3). This thesis also explores how SMEs implemented BI&A. The study suggests data lake technology is an agile and affordable BI&A environment for SMEs as part of an iterative approach. In addition, implementing data lake complements the limitations of the traditional data management tools in BI&A (Paper 4). I also proposed a set of recommendations contributing to successful BI&A adoption and value creation. Research approaches supporting the objectives are presented as methodological contributions.

7.2 Limitations and Suggestions for Future Research

This section discusses the study's limitations and provides suggestions for future research. Despite its potential for delivering a rich and better understanding of BI&A adoption, this thesis has some limitations. First, targeting only experts in the Delphi study and interviews may give a limited picture of BI&A adoption and may not emerge from conducting only qualitative expert interviews and a Delphi study. Conducting in-depth case studies of one or more SMEs might provide a deeper understanding of the topic. The second limitation is my treatment of SMEs as a uniform group of organizations. A study with a more granular observation of enterprise size, ownership, or industry differences may yield more detailed findings. Finally, the study was performed in only one country. It would be interesting to determine whether the study's findings are generalizable to other countries.

The thesis' limitations offer future research suggestions. By demonstrating the implementation, utilization, and value creation of BI&A, the thesis can be a foundation for further research on BI&A adoption in SMEs. The focus of the thesis was to better understand BI&A adoption in SMEs. Most SMEs adopted BI&A tools without data warehouse and BI&A with automated data warehouse. I posit there is a need for empirical studies to assess the two approaches' validity and what can make BI&A more mainstream in SMEs. It is also crucial to consider the difference between the small enterprise and the medium-sized enterprise. Future work can also focus on utilizing other IS theories not presented in this thesis, to understand BI&A's role in organizational performance.

Most SMEs only utilized BI&A for reporting and simple analytics, therefore further studies should assess SMEs' readiness and capabilities for BI&A and how BI&A is utilized in various industries. The perceptions about potential business value are important to understand BI&A adoption. Thus, the study's findings identified critical implementation drivers for BI&A value creation. I believe future research should focus more on how these identified drivers, like building a business case and data governance, influence BI&A value creation process in SMEs. Future research should also explore the novel cost-effective approaches to BI&A, like data lake technology. Such insights can have practical implications.

Finally, the Delphi study results offer several future research topics. The identified drivers and inhibitors provide possibilities for quantitative studies to test the relationships between the core issues, and other influencing factors and capabilities. Future research should also focus on the role of an analytical-friendly culture in SMEs' decision-making environments. A better understanding of the identified core drivers and inhibitors could be gained from longitudinal studies through examining adoption processes over time by focusing on SMEs' BI&A life cycles, value creation, and organizational performance.

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Appendices

Appendix A: Documentation of Data Collection

1. Brainstorming Survey
2. Narrowing-Down Survey
3. Ranking Survey
4. Re-ranking Survey
5. Interview Guidelines

DELPHI STUDY ROUND 1

Business Intelligence Adoption in Small and Medium Sized Enterprises: Brainstorming Phase

Introduction

Thank you for agreeing to participate in this Delphi study on Business Intelligence adoption in Norway. This questionnaire is the first of three rounds of the study. Please try to answer all questions, even though we do not expect you to have in depth knowledge of all of them.

Once we have received the responses from all the panel of experts, we will collate and summarize the findings to generate a questionnaire for use in Round two. You will have the opportunity to revise your answers with subsequent rounds of the survey.

We assure you that your participation in this study and your individual responses will be strictly confidential to the research team and will not be divulged to any outside party, including other panelists. Your time and expertise are very much appreciated.

Questionnaire

Round One will consist of open-ended questions designed to draw on a wide range of knowledge, ideas, and opinions. In case the questions are not clear to you, please do not hesitate to contact us. Our contact details can be found on the next page.

Please keep the following in mind when answering the first round of Delphi study:

- You can write your answers preferably using another font color.
- Any idea is open for discussion, which means that all ideas that come to your mind can be written down.
- Please answer honestly, providing as much detail as possible, to allow a greater depth of knowledge and ideas to be collated for future rounds.
- Small and Medium-sized enterprises (SMEs) are identified by employment size as enterprises with fewer than 250 persons employed.

Self-Assessment

The following are meant to identify the collective experience of the panel of experts. Please fill in the following information if applicable:

Profession	
Email address	
Contact number	
Years of experience in BI	
Number of BI projects participated in	

Research Team

UiA University of Agder

Marilex Rea Llave
PhD Research Fellow
Tel: 38 14 24 28
Marilex.r.llave@uia.no
Department of Information Systems
Faculty of Social Sciences

Dag H. Olsen
Professor
Tel: 38 14 17 06
Dag.h.olsen@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Eli Hustad
Professor
Tel: 38 14 16 21
Eli.hustad@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Delphi Study Round 1 Questionnaire

Q1: What are the drivers (different factors contributing to adoption) of SME BI&A adoption?

- Provide at least 5 drivers and feel free to add more rows if necessary.

Drivers	Comments

Q2: What are the inhibitors (challenges, problems) of SME BI&A adoption?

- Provide at least 5 inhibitors and feel free to add more rows if necessary.

Inhibitors	Comments

Delphi Study Round 2 Validation

Please review the two lists, to see if you agree with the items. Some of the proposed items from the Round 1 questionnaire were success factors for BI implementation rather than *drivers* or *inhibitors* for BI adoption. Those items were not included in the final list.

1. Drivers in Business Intelligence Adoption

	Drivers	Comments
Technological	1. The need for deeper data insight	➢ A need to gain more insight into internal data (revenue, cost, profitability, customers, etc.) ➢ Lots of operational or administrative systems with useful data, different business rules and base for comparison in line of business. ➢ To understand the total picture of the business.
	2. The need for data integration	➢ A need to consolidate data from disparate sources/systems. ➢ Integrate information from different departments, business components, etc. ➢ Seeing information in combination with other types of data for analysis and correlation.
	3. The desire for data quality and structure	➢ To take control of data quality such that reporting is consistent throughout the company ➢ Without it trust in any system will suffer ➢ With poor data, the time and focus can slow the project. ➢ Focus on data quality content not so much visualization. ➢ Having these could give the developer a flying start in the development of the solution.
	4. The need for data visualization	
	5. The need for current and accurate information	➢ The reliability of information assembled ➢ Fact based information. To let operators to see what input and the results of their interaction with the

		tool they use in their part of a process.
	6. The need for standardization	➢ To reduce overlapping tools, since more tools the organization have, the harder it is to get full understanding of the business. ➢ Standardization can lower costs.
	7. To extend existing solutions (e.g. ERP, CRM, MS excel, etc.) with BI capabilities	➢ ERP system do not provide sufficient data structure for creating reports. ➢ CRM needs analytical data. ➢ New ERP systems. ➢ To have something robust than excel.
	8. The need for the single version of truth	➢ To avoid people coming up with different numbers on the same reporting task.
	9. Information overflow leads to a need for BI	
	10. The emergence of Internet of things (IoT)	➢ To analyze data from internet of things for better measure and performance optimization.
	11. User-friendly BI tools.	➢ Easy to use BI tools in the market
Organizational	12. BI is an executive priority	➢ Management Support. ➢ Executive support
	13. Knowledge and experience on BI tools and products	
	14. The need to improve organizational efficiency	➢ Improve efficiency.
	15. The desire to become a data driven organization	➢ The need to make the information available to everyone ➢ Increased access to information ➢ Data in Silos, all companies complain that not all data is accessible ➢ To lessen the complaints regarding data accessibility. ➢ To improve the quality of decision based on facts not gut feeling. ➢ Easy decision-making
	16. The need for creating better/intelligent products and services	➢ Create better products, improved products, productivity supply chain operation and marketing. ➢ Embedding BI in the customer offerings to make intelligent products.

		➢ Insight to drive strategy processes and product development, which can be derived from customer behavior, support calls, and other touchpoints.
	17. The desire to improve performance management	➢ To measure and manage performance of organization. ➢ To have control on profit and loss report to all departments.
	18. The need to achieve a richer reporting capacity	➢ Efficient/Improve reporting because the current business reporting is time consuming. ➢ Flexibility of reports and analytics
	19. The need to automate data management and reporting	➢ A need to automate manual reporting procedures, to free up resources from creating reports/analyses to focus on interpreting the data. ➢ The need to cut down on manual data processing. ➢ Automate report production/reduce cost. Reduce manual processing and operational risk.
	20. BI awareness	➢ Empowered employees who is aware of BI capabilities.
	21. BI champion	➢ Power users who will embrace BI solutions or who has a drive for BI.
	22. The desire to increase profitability	➢ Removal of unprofitable products, outlets, etc. ➢ Reduce cost/cost management cutting. Added business value and gives new product sales.
	23. Risk mitigation	➢ Use BI to avoid or minimize risk.
	24. The need to increase competitive advantage.	➢ To increase competitive power and to protect sustainable competitive advantage.
	25. The desire to improve enterprise performance.	➢ Better overview of the business and identify business value. To easily penetrate markets. ➢ Understanding the business strengths and weaknesses. ➢ Identify sales channels, products, and strategies. ➢ To improve market insight and discover market trends. ➢ Foresight - A need to predict the future to take appropriate action (revenue, costs, customer churn).

		➢ Need for information to support development and growth. ➢ Identify business value, productivity and sales ➢ Increase business and market share by identifying growth opportunities
	26. The need to achieve an effective decision-making at all levels of organization	➢ Making better and informed business decision in a timely fashion.
	27. The desire to improve customer service excellence and customer insight	➢ To increase customer satisfaction, reduce/identify churn probability, and customer retention. ➢ The need for report as product to customers. To know what the customer says, customer insight to increase sales.
	28. Owner demand	➢ Requirements from owner
	29. BI is a priority within organization	➢ Priority within organization
	30. The desire to keep up with the technology improvement	➢ Technology improvement.
	31. The need for organization's internal control	➢ Need for internal control and guided analytics to drive the entire company in same direction. ➢ Better control of KPI's and important numbers for the business.
	32. The desire to be perceived as advanced technology user.	➢ People love to talk what they've done as a company or otherwise.
Environmental	33. Legal compliance	➢ Legal compliance is business critical. Your company will be shut down if you neglect reporting. ➢ Mandatory reporting to the government especially in finance industry.
	34. Change in the competitive landscape	➢ For stronger competition in the marketplace. ➢ Differentiate from competitors.

	35. Decreasing BI technology cost	➢ Price is important when it comes to the decision if one wants to implement a BI solution. ➢ Traditional BI tools are often quite expensive and require significant resources to set up. ➢ Cheaper BI technology
	36. Success stories within large enterprises	
	37. Market hype	➢ Afraid of falling behind the rest of competitors. ➢ Market hype such as cloud, open source, data science.
	38. Emergence of General Data Protection Regulation (GDPR)	➢ This may influence BI in a good way.

2. Inhibitors in Business Intelligence Adoption

	Inhibitors	Comments
Technological	1. Data security concerns	➢ Who will be allowed to see what information
	2. BI project complexity	➢ Endless stream of change during implementation. ➢ Time and focus to implement
	3. Poor data quality	➢ Without good data quality, the trust in BI suffers. ➢ Data quality is low, and the users do not trust the data, decision-making could be taken out of false premises.
	4. Difficulty on selecting the appropriate BI tools	➢ The difficulty on finding the right software or already used wrong BI tools. ➢ Using or have used the wrong tool. ➢ Finding the right tool.
	5. BI tools complexity	➢ Interface complexity of BI tools. ➢ BI technology is too difficult to learn.
Organizational	6. Limited resources	➢ SMEs lacks financial strength, has tight budgets. ➢ Lack of sponsors to have the money for BI implementation
	7. Lack of knowledge about BI tools and products	➢ They do not know how to utilize the tool and do not understand why they need it. ➢ No general overview of having BI solution. ➢ Lack of experience and understanding possibilities.
	8. Lack of technology competence	➢ It is part of BI demands. ➢ Smaller business is likely to have commodity software, that may be difficult to adjust for BI solution and needs.
	9. Lack of BI competence/skills	➢ Cannot maintain BI solutions due to this. ➢ Do not have the right skills in IT or business department. ➢ Usually SMEs have shortage on people including BI skills. ➢ Users IT knowledge maybe challenging for adapting to new tools ➢ Low internal BI competence and skills. ➢ Lack of internal BI community.
	10. Lack of BI awareness	➢ Not being aware of BI possibilities and failure to see the value of BI. ➢ Not aware of Bi existence

	11. Difficulty on realizing the benefits of BI	➢ No understanding on real benefits of BI. ➢ Spending before results.
	12. BI is not an executive priority.	
	13. Implementation time requirements	➢ Time for execution and time for organization to assess. ➢ Time required for training the personnel.
	14. Technophobia	➢ Do not trust the systems and afraid of losing control. ➢ Skeptic to IT investments.
	15. Resistance to change	➢ Keeping the old habits and resistance to change. ➢ Changing user’s mindset.
	16. BI is not business priority	➢ BI is not the top priority for smaller companies. ➢ Small companies have small data and few systems which makes BI appear less relevant.
	17. Difficulty on building effective use cases	➢ Lack of knowledge on how to get ROI or clear use cases.
	18. Lack of analytical culture	➢ No culture for analysis and BI.
	19. Lack of BI champion	➢ People who can push the project to completion. ➢ People who has drive for BI.
	20. Data sharing and accessing issues	➢ Unwilling to share the data. ➢ This is our data, does anybody else need those?
	21. SMEs’ volume of data is too small and few business cases	
	22. Internal competition for resources	➢ Between IT and business people.
	23. BI requires organizational change	➢ Adopting BI tools as a central part of your organization requires a significant amount of change in how the organization uses and acquires information.

	24. Perceptions of BI as a backward-looking technology	➢ Based the business strategy on yesterday information and not on the future impacts ➢ The business activities are based on existing data. The organization may ignore important internal/external influences that can have impact on the business. ➢ Creativity in the organization can be undermined as the business vision and strategy are based on current information.
	25. BI project scope creep	➢ Many BI projects wanted to cover too many KPIS's, measures, and report requirements. ➢ BI projects become too extensive.
	26. Organizational Power Mechanisms	➢ Politics regarding technology adoption decision.
Environmental	27. Risk for failure	➢ High risks of failure ➢ Bad reputation ➢ Few success stories
	28. Cost of BI tools and consulting	➢ Upfront, setup, running, and maintenance cost. ➢ BI project implementation and operational cost, training cost.
	29. BI vendors have business models not tailored for small accounts.	

DELPHI STUDY ROUND 2

Business Intelligence Adoption in Small and Medium Sized Enterprises: Narrowing Down Phase

Introduction

Thank you for continuing to participate in this Delphi study on Business Intelligence (BI) adoption in Norway. This questionnaire is the second of three rounds of the study.

After completing the first round which is the brainstorming phase, our research team have worked to bring together and collate all the responses of the BI experts participating in this study. Answers that did not satisfy the questions from round 1 were not considered. Duplicate answers were removed to reduce the total number of items proposed to a pre-final compiled list of 38 drivers and 29 inhibitors.

Before sending out the round 2 study, we asked all the BI experts to validate the pre-final list generated at this stage. We really appreciate all the comments and feedbacks that yield to the final list of drivers and inhibitors in BI adoption.

The goal of this second round is to understand the rating of importance of the items based on the differing perspectives of various BI experts. In this round, we will narrow down factors that reflect the perspectives of the constituent BI experts to facilitate consensus in the third (last) round.

We assure you that your participation in this study and your individual responses will be strictly confidential to the research team and will not be divulged to any outside party, including other panelists. Your time and expertise is very much appreciated.

Questionnaire

For this second round, you will see the list of 38 drivers and 29 inhibitors with some comments to further explain each item. We would like you to select at least **10 drivers** and **10 inhibitors** that you considered to be most important. If you find yourself considering **more than 10 items**, we will allow you to select up to **15 drivers and 15 inhibitors**. In selecting the items, please kindly mark the column "**Important**" by letter "**X**".

In case the instructions are not clear to you, please do not hesitate to contact us. Our contact details can be found on the next page.

Please keep the following in mind when answering the second round of Delphi study:

- **Small and Medium-sized enterprises (SMEs)** are identified by employment size as enterprises with fewer than 250 persons employed.
- **Drivers** are factors that influence SMEs to adopt BI technologies while **inhibitors** are factors that influence SMEs not to adopt BI technologies.
- **Technological drivers** are the needs to improve the operation in an organization due to the limitation of the existing systems which drives system adoption. While **technological inhibitors** are technological incompetence/limitation of an organization that hinders system adoption.
- **Organizational drivers** are factors that show the compatibility or fit between systems and organization's processes that leads to system adoption while **organizational inhibitors** are the limitation of the organization that will not yield to system adoption.
- **Environmental drivers** are external pressure by its environment exerted in an organization that can result to system adoption while **environmental inhibitors** are external pressure that inhibits system adoption.

Research Team

Marilex Rea Llave
PhD Research Fellow
Tel: 38 14 24 28
Mob: 94 12 50 64
Marilex.r.llave@uia.no
Department of Information Systems
Faculty of Social Sciences

Dag H. Olsen
Professor
Tel: 38 14 17 06
Dag.h.olsen@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Eli Hustad
Associate Professor
Tel: 38 14 16 21
Eli.hustad@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Delphi Study Round 2 Narrowing Down

Some of the proposed items from the Round 1 questionnaire were success factors for BI implementation rather than drivers or inhibitors for BI adoption. Therefore, those items were not included in the final list.

1. Drivers in Business Intelligence Adoption

*Mark the column "**Important**" by letter "**X**"*

	Drivers	Comments	Important
Technological	1. The need for deeper data insight	➢ A need to gain more insight into internal data (revenue, cost, profitability, customers, etc.) ➢ Lots of operational or administrative systems with useful data, different business rules and base for comparison in line of business. ➢ To understand the total picture of the business.	
	2. The need for data integration	➢ A need to consolidate data from disparate sources/systems. ➢ Integrate information from different departments, business components, etc. ➢ Seeing information in combination with other types of data for analysis and correlation.	
	3. The desire for data quality and structure	➢ To take control of data quality such that reporting is consistent throughout the company. ➢ Without it trust in any system will suffer. ➢ With poor data, the time and focus can slow the project.	

		➢ Focus on data quality content not so much visualization. ➢ Having these could give the developer a flying start in the development of the solution.	
	4. The need for data visualization	➢ The need for tools that provides out of the box graphical techniques that are easy to apply on quantitative data is a typical driver to invest BI tools.	
	5. The need for updated and accurate information	➢ The reliability of information assembled ➢ Fact based information. To let operators to see what input and the results of their interaction with the tool they use in their part of a process.	
	6. Standardization		
	7. To extend existing solutions (e.g. ERP, CRM, MS excel, etc.) with BI capabilities	➢ ERP system do not provide sufficient data structure for creating reports. ➢ CRM needs analytical data. ➢ New ERP systems. ➢ To have something robust than excel.	
	8. The need for the single version of truth	➢ To avoid people coming up with different numbers on the same reporting task.	
	9. Information overflow leads to a need for BI		
	10. The emergence of Internet of things (IoT)	➢ To analyze data from internet of things for better measure and performance optimization.	

	11. User-friendly BI tools.	➢ Easy to use BI tools in the market.	
Organizational	12. BI is an executive priority	➢ Management Support. ➢ Executive support.	
	13. Knowledge and experience on BI tools and products	➢ Knowledgeable employees lead to internal sponsors for BI.	
	14. The need to improve organizational efficiency	➢ Improve efficiency. ➢ Both core, support, and management processes.	
	15. The desire to become a data driven organization	➢ The need to make the information available to everyone. ➢ Increased access to information. ➢ Data in Silos, all companies complain that not all data is accessible. ➢ To lessen the complaints regarding data accessibility. ➢ To improve the quality of decision based on facts not gut feeling. ➢ Easy decision-making.	
	16. The need for creating better/intelligent products and services	➢ Create better products, improved products, productivity supply chain operation and marketing. ➢ Embedding BI in the customer offerings to make intelligent products. ➢ Insight to drive strategy processes and product development, which can be derived from customer behavior, support calls, and other touchpoints.	
	17. The need to achieve a richer reporting capacity	➢ Efficient/Improve reporting because the current business	

		reporting is time consuming. ➢ Flexibility of reports and analytics.	
	18. The need to automate data management and reporting	➢ A need to automate manual reporting procedures, to free up resources from creating reports/analysis' to focus on interpreting the data. ➢ The need to cut down on manual data processing. ➢ Automate report production/reduce cost. ➢ Reduce manual processing and operational risk.	
	19. BI awareness	➢ Empowered employees who is aware of BI capabilities.	
	20. BI champion	➢ Power users who will embrace BI solutions or who has a drive for BI.	
	21. The desire to increase profitability	➢ Removal of unprofitable products, outlets, etc. ➢ Reduce cost/cost management cutting. Added business value and gives new product sales.	
	22. Risk mitigation	➢ BI tools have been used for enhancing risk management.	
	23. The desire to improve performance management	➢ To measure and manage performance of organization. ➢ To have control on profit and loss report to all departments.	
	24. The need for organization's internal control	➢ Need for internal control and guided analytics to drive the entire company in same direction. ➢ Better control of KPI's and important numbers for the business.	

	25. The need to increase competitive advantage.	➢ To increase competitive power and to protect sustainable competitive advantage.	
	26. The desire to improve enterprise performance.	➢ Better overview of the business and identify business value. To easily penetrate markets. ➢ Understanding the business strengths and weaknesses. ➢ Identify sales channels, products, and strategies. ➢ To improve market insight and discover market trends. ➢ Foresight - A need to predict the future to take appropriate action (revenue, costs, customer churn). ➢ Need for information to support development and growth. ➢ Identify business value, productivity and sales Increase business and market share by identifying growth opportunities	
	27. The need to achieve an effective decision-making at all levels of organization	➢ Making better and informed business decision in a timely fashion. ➢ Drive new arenas for decision-making. Especially operational focus aligned with strategy.	
	28. The desire to improve customer service excellence and customer insight	➢ To increase customer satisfaction, reduce/identify churn probability, and customer retention. ➢ The need for report as product to customers.	

		To know what the customer says, customer insight to increase sales.	
	29. Owner demand	➢ Requirements from owner.	
	30. BI is a priority within organization	➢ Priority within organization	
	31. The desire to keep up with the technology improvement	➢ Technology improvement.	
	32. The desire to be perceived as advanced technology user.	➢ People love to talk what they've done as a company or otherwise.	
Environmental	33. Legal compliance	➢ Legal compliance is business critical. Your company will be shut down if you neglect reporting. ➢ Mandatory reporting to the government especially in finance industry.	
	34. Change in the competitive landscape	➢ For stronger competition in the market place. ➢ Differentiate from competitors.	
	35. Decreasing BI technology cost	➢ Price is important when it comes to the decision if one wants to implement a BI solution. ➢ Traditional BI tools are often quite expensive and require significant resources to set up. ➢ Cheaper BI technology	
	36. Success stories within other enterprises		
	37. Market hype	➢ Afraid of falling behind the rest of competitors.	

		➢ Market hype such as cloud, open source, data science.	
	38. Emergence of General Data Protection Regulation (GDPR)	➢ This will influence BI in a good way. <BI consultancy companies are concerned with this, which is good news.	

2. Inhibitors in Business Intelligence Adoption

*Mark the column "**Important**" by letter "**X**"*

	Inhibitors	Comments	Important
Technological	1. Data security concerns	➢ Who will be allowed to see what information	
	2. BI project complexity	➢ Endless stream of change during implementation. ➢ Time and focus to implement	
	3. Poor data quality	➢ Poor data quality will give limited value for BI. ➢ Without good data quality, the trust in BI suffers. ➢ Data quality is low and the users do not trust the data, decision-making could be taken out of false premises.	
	4. Difficulty on selecting the appropriate BI tools	➢ The difficulty on finding the right software or already used wrong BI tools. ➢ Using or have used the wrong tool. ➢ Finding the right tool.	
	5. BI tools complexity	➢ Interface complexity of BI tools. ➢ BI technology is too difficult to learn.	
Organizational	6. Limited resources	➢ SMEs lacks financial strength, has tight budgets. ➢ Lack of sponsors to have the money for BI implementation	
	7. Lack of knowledge about BI tools and products	➢ They do not know how to utilize the tool and do not understand why they need it. ➢ No general overview of having BI solution.	

		➢ Lack of experience and understanding possibilities.	
	8. Lack of technology competence	➢ It is part of BI demands. ➢ Smaller business is likely to have commodity software, that may be difficult to adjust for BI solution and needs.	
	9. Lack of BI competence/skills	➢ Cannot maintain BI solutions due to this. ➢ Do not have the right skills in IT or business department. ➢ Usually SMEs have shortage on people including BI skills. ➢ Users IT knowledge maybe challenging for adapting to new tools ➢ Low internal BI competence and skills. ➢ Lack of internal BI community.	
	10. Lack of BI awareness	➢ Not being aware of BI possibilities and failure to see the value of BI. ➢ Not aware of Bi existence	
	11. Difficulty on realizing the benefits of BI	➢ No understanding on real benefits of BI. ➢ Spending before results.	
	12. BI is not an executive priority.		
	13. Implementation time requirements	➢ Time for execution and time for organization to assess. ➢ Time required for training the personnel.	

	14. Technophobia	➢ Do not trust the systems and afraid of losing control. ➢ Skeptic to IT investments.	
	15. Resistance to change	➢ Keeping the old habits and resistance to change. ➢ Changing user’s mindset.	
	16. BI requires organizational change	➢ Adopting BI tools as a central part of your organization requires a significant amount of change in how the organization uses and acquires information.	
	17. BI is not business priority	➢ BI is not the top priority for smaller companies. ➢ Small companies have small data and few systems which makes BI appear less relevant.	
	18. Difficulty on building effective use cases	➢ Lack of knowledge on how to get ROI or clear use cases.	
	19. Lack of analytical culture	➢ No culture for analysis and BI.	
	20. Lack of BI champion	➢ People who can push the project to completion. ➢ People who has drive for BI.	
	21. Data sharing and accessing issues	➢ Unwilling to share the data. ➢ This is our data, does anybody else need those?	
	22. SMEs’ volume of data is too small and few business cases	➢ Having small data makes BI appear less relevant.	
	23. Internal competition for resources	➢ Between IT and business people.	

	24. Perceptions of BI as a backward-looking technology	➢ Based the business strategy on yesterday information and not on the future impacts ➢ The business activities are based on existing data. The organization may ignore important internal/external influences that can have impact on the business. ➢ Creativity in the organization can be undermined as the business vision and strategy are based on current information.	
	25. BI project scope creep	➢ Many BI projects wanted to cover too many KPIS's, measures, and report requirements. ➢ BI projects become too extensive.	
	26. Organizational Power Mechanisms	➢ Politics regarding technology adoption decision. ➢ Company politics.	
Environmental	27. Risk for failure	➢ High risks of failure ➢ Bad reputation ➢ Few success stories	
	28. Cost of BI tools and consulting	➢ Upfront, setup, running, and maintenance cost. ➢ BI project implementation and operational cost, training cost.	
	29. BI vendors have business models not tailored for small accounts.	➢ They typically focus on large customers which affects the pricing and complexity of BI solutions.	

DELPHI STUDY ROUND 3

Business Intelligence Adoption in Small and Medium Sized Enterprises: Ranking Phase

Introduction

Thank you for continuing to participate in this Delphi study on Business Intelligence (BI) adoption in Norway. This questionnaire is the final phase of the study.

In the previous round Narrowing down, we asked each BI expert to select at least 10 items on each list that they believe are the most important for them. The second round aims to narrow the list of drivers and inhibitors to a manageable number, so that in the next phase, these drivers and inhibitors will be meaningfully ranked.

The goal of this phase is to determine the relative importance of the identified drivers and inhibitors, we therefore ask each expert **to rank each item in the list of drivers and inhibitors**.

We assure you that your participation in this study and your individual responses will be strictly confidential to the research team and will not be divulged to any outside party, including other panelists. Your time and expertise are very much appreciated.

Questionnaire

For this third round, **you will rank the following 18 drivers and 18 inhibitors**. **It is only allowed to have one item per rank on each list. Please submit any comments to explain or justify your rankings in the comment box below each list (optional)**.

In case the instructions are not clear to you, please do not hesitate to contact us. Our contact details can be found on the next page. Please keep the following in mind when answering the third round of Delphi study:

- **Small and Medium-sized enterprises (SMEs)** are identified by employment size as enterprises with fewer than 250 persons employed.
- **Drivers** are factors that influence SMEs to adopt BI technologies while **inhibitors** are factors that influence SMEs not to adopt BI technologies.

Research Team

Marilex Rea Llave
PhD Research Fellow
Tel: 38 14 24 28
Mob: 94 12 50 64
Marilex.r.llave@uia.no
Department of Information Systems
Faculty of Social Sciences

Dag Håkon Olsen
Professor
Tel: 38 14 17 06
Dag.h.olsen@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Eli Hustad
Professor
Tel: 38 14 16 21
Eli.hustad@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Delphi Study Round 3 Ranking

Example:

Who is your favorite Game of Thrones character?

*Mark the column **"Ranking"** by numbers **"1-5 where 1 is the highest"***

Game of Thrones Character	**Ranking**
1. Cersei Lannister	*5*
2. Daenerys Targaryen	*2*
3. Jon Snow	*1*
4. Tyrion Lannister	*3*
5. Jaime Lannister	*4*

Comments:
1 – Jon Snow is a man of honor that's why he is the best! 2 – Daenerys can ride dragons and can say DRACARYS!! And that is cool! 3 – Tyrion is a tactful and clear-sighted man!! 4 – Jaime is a brilliant example of character development. 5 – Cersei is just ruthless.

1. Drivers in Business Intelligence Adoption

*Mark the column **"Ranking"** by numbers **"1-18, where 1 is the most important"***

Drivers	Comments	Ranking
1. The need for deeper data insight	➢ A need to gain more insight into internal data (revenue, cost, profitability, customers, etc.) ➢ Lots of operational or administrative systems with useful data, different business rules and base for comparison in line of business. ➢ To understand the total picture of the business.	

2. The need for data integration	➢ A need to consolidate data from disparate sources/systems. ➢ Integrate information from different departments, business components, etc. ➢ Seeing information in combination with other types of data for analysis and correlation.	
3. The desire to improve enterprise performance.	➢ Better overview of the business and identify business value. To easily penetrate markets. ➢ Understanding the business strengths and weaknesses. ➢ Identify sales channels, products, and strategies. ➢ To improve market insight and discover market trends. ➢ Foresight - A need to predict the future to take appropriate action (revenue, costs, customer churn). ➢ Need for information to support development and growth. ➢ Identify business value, productivity and sales ➢ Increase business and market share by identifying growth opportunities	
4. The desire for data quality and structure	➢ To take control of data quality such that reporting is consistent throughout the company. ➢ Without it trust in any system will suffer. ➢ With poor data, the time and focus can slow the project. ➢ Focus on data quality content not so much visualization. ➢ Having these could give the developer a flying start in the development of the solution.	
5. The need to improve organizational efficiency	➢ Improve efficiency. ➢ Both core, support, and management processes.	

6. The desire to become a data driven organization	➢ The need to make the information available to everyone. ➢ Increased access to information. ➢ Data in Silos, all companies complain that not all data is accessible. ➢ To lessen the complaints regarding data accessibility. ➢ To improve the quality of decision based on facts not gut feeling. ➢ Easy decision-making.	
7. The need for updated and accurate information	➢ The reliability of information assembled ➢ Fact based information. To let operators to see what input and the results of their interaction with the tool they use in their part of a process.	
8. The need for the single version of truth	➢ To avoid people coming up with different numbers on the same reporting task.	
9. The need to achieve an effective decision-making at all levels of organization	➢ Making better and informed business decision in a timely fashion. ➢ Drive new arenas for decision-making. Especially operational focus aligned with strategy.	
10. The need to increase competitive advantage.	➢ To increase competitive power and to protect sustainable competitive advantage.	
11. The need to automate data management and reporting	➢ A need to automate manual reporting procedures, to free up resources from creating reports/analysis' to focus on interpreting the data. ➢ The need to cut down on manual data processing. ➢ Automate report production/reduce cost. Reduce manual processing and operational risk.	
12. BI is an executive priority	➢ Management Support. ➢ Executive support.	
13. Emergence of General Data Protection Regulation (GDPR)	➢ This will influence BI in a good way. BI consultancy companies are	

	concerned with this, which is good news.	
14. Legal compliance	➢ Legal compliance is business critical. Your company will be shut down if you neglect reporting. ➢ Mandatory reporting to the government especially in finance industry.	
15. The need for data visualization	➢ The need for tools that provides out of the box graphical techniques that are easy to apply on quantitative data is a typical driver to invest BI tools.	
16. The desire to increase profitability	➢ Removal of unprofitable products, outlets, etc. ➢ Reduce cost/cost management cutting. ➢ Added business value and gives new product sales.	
17. The desire to improve performance management	➢ To measure and manage performance of organization. ➢ To have control on profit and loss report to all departments.	
18. The desire to improve customer service excellence and customer insight	➢ To increase customer satisfaction, reduce/identify churn probability, and customer retention. ➢ The need for report as product to customers. ➢ To know what the customer says, customer insight to increase sales.	

Comments:	**My ranking and comments**

2. Inhibitors in Business Intelligence Adoption

*Mark the column **"Ranking"** by numbers **"1-18 where 1 is the most important"***

Inhibitors	Comments	Ranking
1. Limited resources	➢ SMEs lacks financial strength, has tight budgets. ➢ Lack of sponsors to have the money for BI implementation	
2. Cost of BI tools and consulting	➢ Upfront, setup, running, and maintenance cost. ➢ BI project implementation and operational cost, training cost.	
3. Lack of BI competence/skills	➢ Cannot maintain BI solutions due to this. ➢ Do not have the right skills in IT or business department. ➢ Usually SMEs have shortage on people including BI skills. ➢ Users IT knowledge maybe challenging for adapting to new tools ➢ Low internal BI competence and skills. ➢ Lack of internal BI community.	
4. Poor data quality	➢ Poor data quality will give limited value for BI. ➢ Without good data quality, the trust in BI suffers. ➢ Data quality is low and the users do not trust the data, decision-making could be taken out of false premises.	
5. Lack of BI awareness	➢ Not being aware of BI possibilities and failure to see the value of BI. ➢ Not aware of Bi existence	
6. Resistance to change	➢ Keeping the old habits and resistance to change. ➢ Changing user's mindset.	
7. Lack of knowledge about BI tools and products	➢ They do not know how to utilize the tool and do not understand why they need it. ➢ No general overview of having BI solution. ➢ Lack of experience and understanding possibilities.	

8. Data security concerns	➢ Who will be allowed to see what information	
9. BI project complexity	➢ Endless stream of change during implementation. ➢ Time and focus to implement	
10. Lack of analytical culture	➢ No culture for analysis and BI.	
11. Lack of BI champion	➢ People who can push the project to completion. ➢ People who has drive for BI.	
12. Lack of technology competence	➢ It is part of BI demands. ➢ Smaller business is likely to have commodity software, that may be difficult to adjust for BI solution and needs.	
13. BI is not an executive priority.		
14. BI project scope creep	➢ Many BI projects wanted to cover too many KPIS's, measures, and report requirements. BI projects become too extensive.	
15. Implementation time requirements	➢ Time for execution and time for organization to assess. ➢ Time required for training the personnel.	
16. BI requires organizational change	➢ Adopting BI tools as a central part of your organization requires a significant amount of change in how the organization uses and acquires information.	
17. Internal competition for resources	➢ Between IT and business people.	
18. BI vendors have business models not tailored for small accounts.	➢ They typically focus on large customers which affects the pricing and complexity of BI solutions.	

Comments:	**My ranking and comments**

DELPHI STUDY ROUND 4

Business Intelligence Adoption in Small and Medium Sized Enterprises: Re-ranking Phase

Introduction

From the previous round of ranking we did not reach the required level of agreement. One of the purposes in a ranking-type Delphi study is to obtain consensus among the participants. Unfortunately, we have a quite low value regarding consensus (low Kendall W value). Therefore, we need to do a new ranking round. This is very important for completing the study and for increasing the validity of the results.

Based on the previous round Ranking Phase, the **average ranking of the issues is provided on the list**. We ask you to kindly **review this list** and **make new ranking adjustments if you do not agree**. **Your previous ranking list is also presented for you to compare with the average**. See the table provided in excel sheet named **"Drivers Re-ranking issues"** and **"Inhibitors Re-ranking issues"**. If you wish to justify your new ranking, or give feedback/comments, please use the "Comments/Justification" area placed beside the table.

For this third round, **you will re-rank the following 18 drivers and 18 inhibitors**. **It is only allowed to have one item per rank on each list. Please submit any comments to explain or justify your rankings in the comment box below each list (optional)**. In case the instructions are not clear to you, please do not hesitate to contact us.

Please keep the following in mind when answering the third round of Delphi study:

- **Small and Medium-sized enterprises (SMEs)** are identified by employment size as enterprises with fewer than 250 persons employed.
- **Drivers** are factors that influence SMEs to adopt BI technologies while **inhibitors** are factors that influence SMEs not to adopt BI technologies.

Research Team

Marilex Rea Llave
PhD Research Fellow
Tel: 38 14 24 28
Mob: 94 12 50 64
Marilex.r.llave@uia.no
Department of Information Systems
Faculty of Social Sciences

Dag Håkon Olsen
Professor
Tel: 38 14 17 06
Dag.h.olsen@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Eli Hustad
Professor
Tel: 38 14 16 21
Eli.hustad@uia.no
Department of Information Systems
Faculty of Social Sciences
University of Agder

Delphi Study Round 4 Re-ranking

Delphi Study on Business Intelligence in Small and Medium-sized Enterprises - Re-Ranking Phase

From the previous round of ranking we did not reach the required level of agreement. One of the purposes in a ranking-type Delphi study is to obtain consensus among the participants. Unfortunately, we have a quite low value regarding consensus (low Kendall W value). Therefore we need to do a new ranking round. This is very important for completing the study and for increasing the validity of the results.

Based on the previous round Ranking Phase, the **average ranking of the issues is provided on the list**. We ask you to kindly **review this list** and **make new ranking adjustments if you do not agree. Your previous ranking list is also presented for you to compare with the average**. See the table provided in excel sheet named **"Drivers Re-ranking issues"** and **"Inhibitors Re-ranking issues"**. If you wish to justify your new ranking, or give feedback/comments, please use the "Comments/Justification" area placed beside the table.

For this third round, **you will re-rank the following 18 drivers and 18 inhibitors**. **It is only allowed to have one item per rank on each list. Please submit any comments to explain or justify your rankings in the comment box below each list (optional)**. In case the instructions are not clear to you, please do not hesitate to contact us.

Please keep the following in mind when answering the third round of Delphi study:
Small and Medium-sized enterprises (SMEs) are identified by employment size as enterprises with fewer than 250 persons employed.
Drivers are factors that influence SMEs to adopt BI technologies while **inhibitors** are factors that influence SMEs not to adopt BI technologies.

Your Panel's average ranking	Your previous ranking	Put your new ranking here
1	1	1
2	8	4
3	22	4

In case you entered duplicate values, the two cells of duplicate values will be highlighted indicating that you need to change either one of the two values

Comments/justifications

Drivers and Comments	Provider Panel Average Rankings	Your Ranking	New Ranking
1. The need for deeper data insight A need to gain more insight into internal data (revenue, cost, profitability, customers, etc.) Lots of operational or administrative systems with useful data, different business rules and base for comparison in line of business. To understand the total picture of the business.	1		
2. The need for data integration A need to consolidate data from disparate sources/systems. Integrate information from different departments, business components, etc. Seeing information in combination with other types of data for analysis and correlation.	3		
3. The desire to improve enterprise performance. Better overview of the business and identify business value. To easily penetrate markets. Understanding the business strengths and weaknesses. Identify sales channels, products, and strategies. To improve market insight and discover market trends. Foresight - A need to predict the future to take appropriate action (revenue, costs, customer churn). Need for information to support development and growth. Identify business value, productivity and sales Increase business and market share by identifying growth opportunities	7		
4. The desire for data quality and structure To take control of data quality such that reporting is consistent throughout the company. Without it trust in any system will suffer. With poor data, the time and focus can slow the project. Focus on data quality content not so much visualization. Having these could give the developer a flying start in the development of the solution.	8		
5. The need to improve organizational efficiency Improve efficiency. Both core, support, and management processes.	2		
6. The desire to become a data driven organization The need to make the information available to everyone. Increased access to information. Data in Silos, all companies complain that not all data is accessible. To lessen the complaints regarding data accessibility. To improve the quality of decision based on facts not gut feeling. Easy decision making.	4		
7. The need for updated and accurate information The reliability of information assembled Fact based information. To let operators to see what input and the results of their interaction with the tool they use in their part of a process.	16		
8. The need for the single version of truth To avoid people coming up with different numbers on the same reporting task.	5		
9. The need to achieve an effective decision making at all levels of organization Making better and informed business decision in a timely fashion. Drive new arenas for decision making. Especially operational focus aligned with strategy.	9		
10. The need to increase competitive advantage. To increase competitive power and to protect sustainable competitive advantage.	10		
11. The need to automate data management and reporting A need to automate manual reporting procedures, to free up resources from creating reports/analysis' to focus on interpreting the data. The need to cut down on manual data processing. Automate report production/reduce cost. Reduce manual processing and operational risk.	11		
12. BI is an executive priority Management Support. Executive support.	6		
13. Emergence of General Data Protection Regulation (GDPR) This will influence BI in a good way. <BI consultancy companies are concerned with this, which is good news.	18		
14. Legal compliance Legal compliance is business critical. Your company will be shut down if you neglect reporting. Mandatory reporting to the government especially in finance industry.	17		
15. The need for data visualization The need for tools that provides out of the box graphical techniques that are easy to apply on quantitative data is a typical driver to invest BI tools.	15		
16. The desire to increase profitability Removal of unprofitable products, outlets, etc. Reduce cost/cost management cutting. Added business value and gives new product sales.	14		
17. The desire to improve performance management To measure and manage performance of organization. To have control on profit and loss report to all departments.	12		
18. The desire to improve customer service excellence and customer insight To increase customer satisfaction, reduce/identify churn probability, and customer retention. The need for report as product to customers. To know what the customer says, customer insight to increase sales.	13		

Inhibitors and Comments	Provider Panel Average Rankings	Your Ranking	New Ranking
1. Limited resources ・SMEs lacks financial strength, has tight budgets. ・Lack of sponsors to have the money for BI implementation	1		
2. Cost of BI tools and consulting ・Upfront, setup, running, and maintenance cost. ・BI project implementation and operational cost, training cost.	3		
3. Lack of BI competence/skills ・Cannot maintain BI solutions due to this. ・Do not have the right skills in IT or business department. ・Usually SMEs have shortage on people including BI skills. ・Users IT knowledge maybe challenging for adapting to new tools ・Low internal BI competence and skills. ・Lack of internal BI community.	2		
4. Poor data quality ・Poor data quality will give limited value for BI. ・Without good data quality, the trust in BI suffers. ・Data quality is low and the users do not trust the data, decision making could be taken out of false premises.	5		
5. Lack of BI awareness ・Not being aware of BI possibilities and failure to see the value of BI. ・Not aware of Bi existence	7		
6. Resistance to change ・Keeping the old habits and resistance to change. ・Changing user's mindset.	11		
7. Lack of knowledge about BI tools and products ・They do not know how to utilize the tool and do not understand why they need it. ・No general overview of having BI solution. ・Lack of experience and understanding possibilities.	13		
8. Data security concerns ・Who will be allowed to see what information	4		
9. BI project complexity ・Endless stream of change during implementation. ・Time and focus to implement	6		
10. Lack of analytical culture ・No culture for analysis and BI.	10		
11. Lack of BI champion ・People who can push the project to completion. ・People who has drive for BI.	9		
12. Lack of technology competence ・It is part of BI demands. ・Smaller business is likely to have commodity software, that may be difficult to adjust for BI solution and needs.	12		
13. BI is not an executive priority.	17		
14. BI project scope creep ・Many BI projects wanted to cover too many KPIS's, measures, and report requirements. BI projects become too extensive.	15		
15. Implementation time requirements ・Time for execution and time for organization to assess. ・Time required for training the personnel.	16		
16. BI requires organizational change ・Adopting BI tools as a central part of your organization requires a significant amount of change in how the organization uses and acquires information.	14		
17. Internal competition for resources ・Between IT and business people.	18		
18. BI vendors have business models not tailored for small accounts. ・They typically focus on large customers which affects the pricing and complexity of BI solutions.	8		

Interview Guide for Exploratory Study and Delphi Study

General Information

- What is your current job?
- When did you start your career in BI&A?
- Can you tell me about the BI&A projects you have participated in?
- In your opinion, what characterizes BI&A adoption in Norway? Any trends?
- What is the standard BI&A tools in Norwegian market?

BI&A Implementation

- Can you describe your implementation experience on BI&A?
- Are they all successful implementation?
- What are the challenges on BI&A implementation?
- What is a successful BI&A implementation for you?
- How do you ensure successful BI&A implementation?
- What is data lake? What are technologies behind the data lake?
- What is the purpose of data lake? Any challenges?
- What are the types of data stored in data lake?
- What are the perceived benefits of data lake?
- Who uses data lake? What type of enterprises?
- Do you think data lake is a necessary investment for SMEs who are BI&A adopters?

BI&A Utilization

- How do SMEs utilize BI&A?
- How do SMEs use BI&A tools like PowerBI and Tableau to achieve their goals?
- How many people are using it?
- Who are the power users of BI&A?
- Can BI&A tools like PowerBI be a technological solution ensuring more efficient work and report production?
- How to support informed decision-making using BI&A?

BI&A Value Creation

- What is the business value of BI&A?
- How does SMEs create business value from BI&A?

- Who creates BI&A solutions’ value, top management, middle managers, or employees?
- What is the business value of BI&A in terms of decision-making process?
- In what way can BI&A be valuable for SMEs?
- What are SMEs’ characteristics influencing the ability to create BI&A investment value?

Follow-up Interview for Delphi Study

- What is your opinion about the final ranked lists of drivers and inhibitors?
- Why are the top drivers and inhibitors important?
- Why are some items more important than others?

Appendix B: Research Publications

1. Paper 1: Llave, M.R., 2019. A Review of Business Intelligence and Analytics in Small and Medium-Sized Enterprises. International Journal of Business Intelligence Research (IJBIR), 10(1), pp.19-41.

2. Paper 2: Llave, M.R., Hustad, E. and Olsen, D.H., 2018. Creating value from business intelligence and analytics in SMEs: insights from experts. In Proceedings of the 24th Americas Conference on Information Systems (AMCIS), New Orleans, Louisiana, USA.

3. Paper 3: Llave, M.R. and Olsen, D., 2018. Drivers of Business Intelligence-based Value Creation: The Experts' View. In Proceedings of the 12th Mediterranean Conference on Information Systems (MCIS), Corfu, Greece.

4. Paper 4: Llave, M.R., 2018. Data lakes in business intelligence: reporting from the trenches. Proceedings of the 10th International Conference on Enterprise Information Systems (CENTERIS), Lisbon, Portugal. Procedia computer science, 138, pp.516-524.

5. Paper 5: Llave, M. R., Hustad, E., & Olsen, D. H. Creating strategic business value from BI&A: Navigating the dire straits between investment and performance (Under Review – Journal of Strategic Information Systems)

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A Review of Business Intelligence and Analytics in Small and Medium-Sized Enterprises

Marilex Rea Llave, University of Agder, Kristiansand, Norway

ABSTRACT

Business intelligence and analytics (BI&A) has become a cornerstone of many organizations in making informed decisions. Despite the importance of small and medium-sized enterprises (SMEs) to all world economies, research in BI&A focuses mostly on large enterprises. To aid in closing this gap, this study provides a comprehensive review of the literature sources in this domain. Through a systematic literature review, this study collects, categorizes, synthesizes, and analyzes 78 articles related to BI&A in SMEs. The research topics that are addressed include BI&A components and solutions, Mobile BI&A, Cloud BI&A, and BI&A application, adoption, implementation, and benefits. Further, the research gaps and suggestions for future research are presented to facilitate the progression of BI&A in SME research.

KEYWORDS

BI&A Adoption, BI&A Benefits, BI&A Implementation, BI&A Solutions, Business Intelligence And Analytics, Cloud BI&A, Mobile BI&A, SMEs

INTRODUCTION

Small and medium-sized enterprises (SMEs) play major economic and social roles because they account for about 90 percent of businesses and more than 50 percent of employment worldwide according to the International Finance Corporation (IFC, 2012, p. 1) Thus, they have become an important source of economic development (Olszak & Ziemba, 2008). The need to improve the worldwide competitiveness of SMEs is crucial. However, SMEs are typically vulnerable and not robust enough to withstand the onslaught of economic and global competition (Ngah, Abd Wahab, & Salleh, 2015). To survive, SMEs must be able to monitor their businesses and use all of their resources efficiently, especially their information resources (Raj, Wong, & Beaumont, 2016).

A substantial difference can be found between SMEs and large enterprises. SMEs usually have limited internal information technology (IT) resources and competencies as well as financial resources. They are also dependent on external expertise when embarking on new IT projects because of the limited human capital and resources for employee training (Blili & Raymond, 1993; Levy & Powell, 2000). SMEs also differ from large enterprises regarding ownership, management, decision making, structure, culture, processes, and procedures. These differences influence SMEs' ability to implement enterprise systems in general (Zach, Munkvold, & Olsen, 2014).

Business intelligence (BI) is an overarching term for decision support systems that are used to collect, analyze, and disseminate organizational data to improve business decision making (Fink,

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Yogev, & Even, 2017). According to Yeoh (2008), the term “business intelligence” was first coined by Luhn (1958). However, as Burstein and Holsapple (2008) recalled, the term was reintroduced by Howard Dresner when he defined it as “a broad category of software and solutions for gathering, consolidating and analyzing, and providing access to data in a way that let enterprise users make better business decisions” (Gibson, Arnott, Jagielska, & Melbourne, 2004).

Business analytics (BA), a more recent term, emerged in the late 2000s, and it focuses on the analytical components of BI (Chen, Chiang, & Storey, 2012). Thus, business intelligence and analytics (BI&A) was developed as a unified term to describe information-intensive concepts and methods of improving decision making in business (Chiang, Goes, & Stohr, 2012). According to a recent Gartner survey, BI&A is the chief information officer’s top technological choice to obtain competitiveness (King, 2016). Chaudhuri, Dayal, and Narasayya (2011) stated that “today, it is difficult to find a successful enterprise that has not leveraged BI&A technology for their business” (p. 91). Therefore, the term BI&A is used for the rest of this paper.

A recent study suggests that SMEs’ limited financial resources have implications for BI&A investment strategies (Llave, Hustad, & Olsen, 2018). Therefore, focusing particularly on SMEs is important to identify the specific benefits and barriers they face when embarking on BI&A initiatives. Notwithstanding its importance, the literature on BI&A in SMEs is lacking (Boonsiritomachai, McGrath, & Burgess, 2016) because the majority of BI&A systems are adopted by large multinational and international enterprises; thus, research on BI&A has largely focused on them (Grabova, Darmont, Chauchat, & Zolotaryova, 2010; Scholz, Schieder, Kurze, Gluchowski, & Böhringer, 2010). Jourdan, Rainer, and Marshall (2008) conducted a literature review on BI&A research. They collected and analyzed articles related to BI&A published from 1997 to 2006 in 10 leading Information Systems (IS) journals. However, their study focused mostly on BI&A in general, not on BI&A in SMEs. An extensive literature search yielded no extant studies that review research on BI&A in SMEs. Therefore, the objective of this paper is to provide a comprehensive review of the literature on BI&A in SMEs. By collecting, analyzing, and synthesizing all extant literature within this domain, this review presents the current state of research topics on BI&A and reveals the prospective gaps that require further research. Specifically, the following research questions guide this review:

RQ1: What research topics of BI&A in SMEs have been addressed in previous research?
RQ2: What are the pertinent research topics on BI&A in SMEs that should be addressed in the future?

Kitchenham’s guidelines for a systematic literature review (SLR) are applied to assess the completeness of the search, achieve effective results, and explain them in a more intelligible manner (Kitchenham, 2004). That is, the research procedures of this review follow a strict sequence and the following well-defined methodological steps: (1) presentation of the search strategy process, (2) identification of the inclusion and exclusion criteria, (3) analysis of the quality assessment, (4) analysis of the selection process, and (5) data extraction and synthesis. Subsequently, 78 selected articles that focus on BI&A in SMEs are reviewed.

The remainder of this work is structured as follows: Section 2 outlines the research methodology procedures used to conduct this research study. Section 3 reports the SLR results, and Section 4 presents the results of the reviewed articles. Section 5 includes a discussion and directions for future research. Finally, Section 6 concludes the research.

RESEARCH METHODOLOGY

This research encompasses an SLR that was undertaken based on the guidelines proposed by Kitchenham (2004). The guidelines offer a structured method of analyzing the status of the literature. In the following sub-sections, the steps followed during the literature review are depicted.

Search Strategy

The search strategy consists of automatic and manual research. In the automatic search the following online databases were queried: Scopus, the Web of Science, IEEE Xplore, ScienceDirect, Taylor and Francis Online, the ACM Digital Library, and Emerald Insight. These databases were selected because they were considered the most pertinent to the research, providing access to high-impact journals and conference proceedings in the field of BI&A.

The use of an online database in the search rather than using a defined set of journals and conferences was empirically driven by suggestions from Dieste and Padua (2007). The keywords used in the search included *business intelligence, business analytics, small business, small and medium enterprise, small and medium-sized enterprises, BI, BA, BI&A,* and *SMEs*, and combinations which were used to identify as many relevant articles as possible. Once the initial data were acquired, the articles were analyzed according to the defined objectives. EndNote was used to store all citations and keep the search results from each database, as well as to circumvent duplicate studies.

In addition to the automatic research, a manual search was performed to ensure that no studies were missed. All the primary studies' references were reviewed while applying the exclusion criteria. The studies obtained from this manual search were added to EndNote, which resulted in the final set of primary studies.

Inclusion and Exclusion Criteria

The purpose of setting the inclusion and exclusion criteria was to ensure that only relevant articles would be included in this study. Peer-reviewed articles from journals, workshops, conference proceedings, and book chapters in the English language that were retrieved from the online databases were considered. Unpublished articles, abstracts, dissertations, theses, and studies published in non-peer-reviewed journals were not included. The articles that were not clearly related to BI&A, were not related to the research questions, or did not have full texts available were eliminated. Duplicate reports of the same studies were also eliminated. When different versions of an article existed, only the complete version of the article was included, and the others were excluded. Note that the selected studies had to satisfy all the inclusion criteria and could not satisfy any exclusion criteria.

Quality Assessment

After determining the inclusion and exclusion criteria, assessing the quality of the primary studies was considered a crucial step (Kitchenham, 2004). The aim of the quality assessment was to assess the overall quality of the selected studies. To guide the interpretation of the findings and determine the strength of the inferences of the selected studies, the following quality assessment questions were used:

QA1: Are the research topics addressed in the paper directly related to BI&A?
QA2: Does the context of the study clearly pertain to SMEs?

Study Selection Process

After the search was conducted, 348 articles were identified. Of these 348 articles, 104 duplicate articles were removed using EndNote. The remaining 244 articles were checked based on the inclusion and exclusion criteria; after that, 147 articles were excluded, and 97 articles remained. Once the first stage of the research was completed, the second could begin. The goal of the manual search was to gain confidence in the comprehensiveness of the search results. Thus, all references from the 97 remaining articles were screened, applying the exclusion criteria, and 17 additional articles were identified. This process of pursuing the references of collected sources is known as backward snowballing (Jalali & Wohlin, 2012; Webster & Watson, 2002). Subsequently, these 17 articles were retrieved through Google Scholar and added to EndNote to produce the pre-final set of primary studies. In total, there were 114 articles. Then, the quality assessment criteria were applied, and 36 articles were removed.

Table 1. Distribution of articles before and after selection process

Online Databases	Before	After
Scopus	164	56
Web of Science	105	7
IEEE Xplore	51	2
ScienceDirect	15	0
Taylor and Francis Online	1	1
ACM Digital Library	9	0
Emerald Insight	3	1
Google Scholar	(17)	11
Total	**365**	**78**

Finally, 78 articles were identified as the final set of primary studies and formed the basis for the next steps in this review. Table 1 presents the distribution of the primary studies and their sources before and after the selection process.

Data Extraction and Synthesis

The process of extracting and synthesizing the collected data was performed by carefully reading each of the 78 articles. The related data were pulled out from these articles and managed using EndNote and MS Excel. The goal of this step was to design data extraction forms to accurately record the information obtained from the primary studies. Consequently, the concept-centric method outlined by Webster and Watson (2002) was used to identify the study context. The other columns considered in this review included the study title, date, research method, number of citations, and publishing location.

SYSTEMATIC LITERATURE REVIEW RESULTS

This section summarizes the necessary statistical results from the selected studies before discussing the data analysis for the SLR in this study. Thus, the publication sources, the citation status, temporal reviews, and applied research methods are presented.

Publication Sources

Most primary studies were published in journals and conference proceedings. Only a few sources were book chapters or material from symposiums and workshops. The distribution of the primary studies according to their publication sources is shown in Figure 1.

Citation Status

An overview of the citation counts of the selected studies is shown in Figure 2. The citation statistics were obtained through Google Scholar and Scopus. By looking at the data presented in Figure 2, it is apparent that 66 of the studies were cited by other sources. Among these studies, only a few had more than 30 citations, while the rest had less than 30 citations or no citations at all. However, this increase in the citation rates can be expected as the majority of the selected studies were published in the last five years.

Figure 1. Distribution per publication source

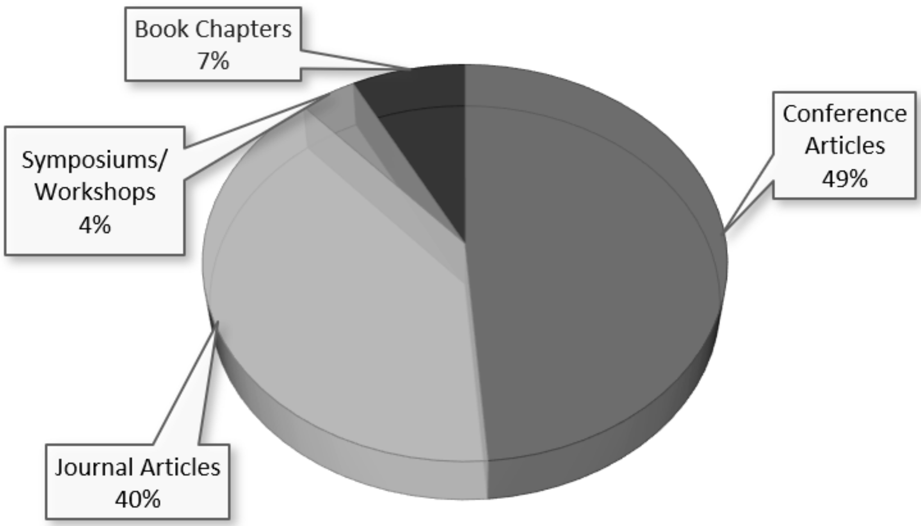
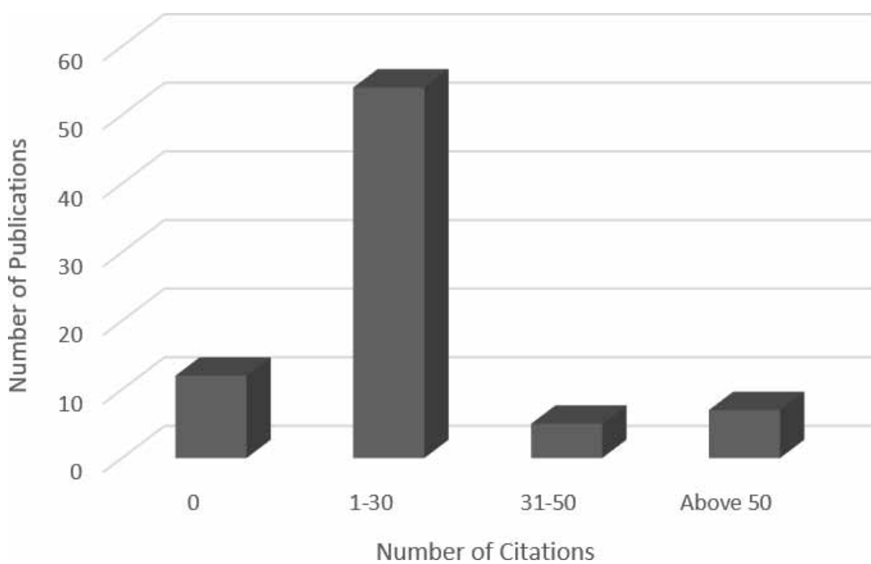


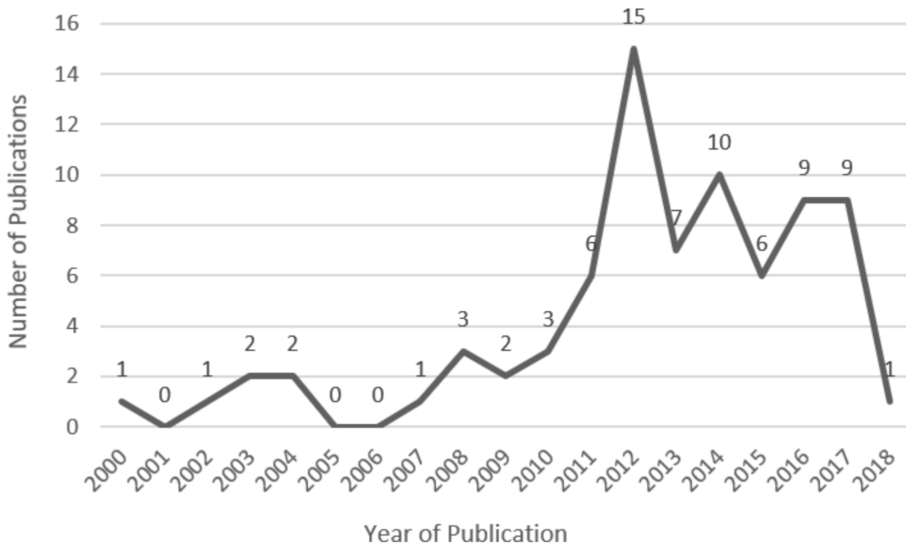
Figure 2. Citation count



Temporal Review

Figure 3 shows the distribution of the final set of selected studies over the years. There was a significant increase in BI&A interest from 2010 to 2012. However, the number of studies decreased from 15 in 2012 to 7 in 2013. Overall, the number of studies included is low. The review was completed in the beginning of 2018, which explains the low number in 2018.

Figure 3. Distribution of the primary studies throughout the years



RESEARCH METHOD

The classification of the included studies with reference to their research methods is shown in Figure 4. By looking at the data presented in Figure 4, it is clear that the research methods in the primary studies were dominated by case studies, followed by surveys, design science research, interviews, descriptive research, and field inquiries. However, out of 78 studies 29 studies did not implicitly or explicitly mention which methods were applied. This suggests that the research field is still immature.

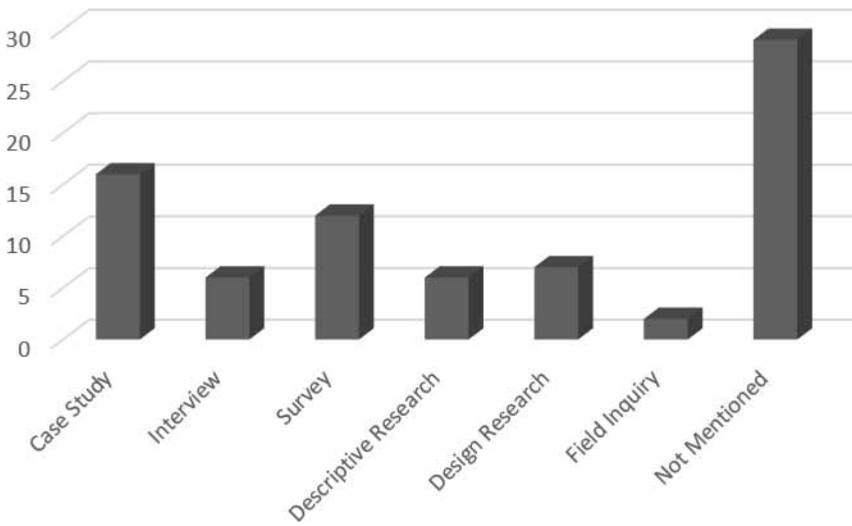
RESULTS

After the primary studies were selected and extracted, it became possible to address this study's RQ1 that was derived from the 78 analyzed articles. A concept-centric method was applied during the data extraction and synthesis phase. The identified research topics were as follows: BI&A components; BI&A solutions; Mobile BI&A; Cloud BI&A; BI&A application; BI&A adoption; BI&A implementation; and BI&A benefits. These topics are summarized in Table 2 and discussed in the following sub-sections.

BI&A Components

A typical BI&A system includes the identification of the key performance indicators (KPIs), data warehousing, data mining, online analytical processing (OLAP), digital dashboards, and reports through data visualization (Ranjan, 2009). Studies have been conducted on data warehouses, KPIs, OLAP, data mining, and dashboards. Sharma, Nasri, and Askand (2012) proposed data warehousing as a service (DaaS) in an attempt to reach a new level of BI&A. Here, the features of web services and data warehousing are combined to implement the proposed architecture. In addition, studies have reported the advantages of DaaS. Pighin and Marzona (2012) investigated the use of data warehousing systems in 45 SMEs in Italy's Udine district, particularly in those of the mechanical sector, one of the most articulated and developed sectors in the region. Grabova et al. (2010) revealed the importance of data warehousing for SMEs and presented two web-based data warehouse technologies: XML document warehouses and XML data warehouses. They also presented the advantages of using web-based data warehouses.

Figure 4. Distribution per research method



Collaborative business systems provide a competitive advantage to companies that operate in joint business structures. However, traditional BI&A is not designed for collaboration. To overcome this shortcoming, Olaru and Vincini (2014) provided an integrated mapping-based methodology for heterogeneous data warehouses. They also argued that latency is a critical issue in data warehousing. Many SMEs refrain from adopting BI&A technology, but reference models enable SMEs to overcome obstacles associated with the introduction of BI&A solutions, as addressed by Schuetz, Neumayr, Schrefl, and Neuböck (2016). Schütz and Schrefl (2014) proposed a four-layer reference model for data warehouses to decrease the obstacles that inhibit SMEs from adopting BI&A technology. Specifically, explicit modeling and calculated KPIs as well as the definition of reference data marts for report building were addressed. Furthermore, Schuetz et al. (2016) addressed the explicit modeling of KPIs by introducing a BI&A reference modeling for data analysis approach.

Another component of BI&A is OLAP, which extracts knowledge from data warehouses and data marts to provide navigation through data for non-expert users. However, traditional OLAP technology is cumbersome, and its storage is costly. To address this issue, Grabova et al. (2010) discussed a number of OLAP technologies that work in the main memory and with web interfaces. They presented three variants of OLAP: MOLAP (multi-dimensional), ROLAP (relational), and HOLAP (hybrid) variants.

BI&A based on data mining has been a popular and indispensable tool for identifying business opportunities in the sales and marketing of new products. Cheung and Li (2012) presented a qualitative correlation coefficient mining method that could uncover hidden patterns in sales and markets. They developed a BI&A prototype called the correlation coefficient sales data mining system. The trial was successful and was implemented at a selected reference site. The results showed that the proposed solution provides greater accuracy, better computational effectiveness, and greater predictive power. Kitayama, Matsubara, and Izui (2002) discussed the use of data mining techniques based on customer profile data in the power electric industry in Japan. The researchers presented an example of a marketing method to establish customer strategies using the data mining technique. Another study by Korczak, Dudycz, and Dyczkowski (2012) implemented an Intelligent Dashboard for Managers called InKoM, which is a dashboard that is an easy-to-read summary that analyzes information. The proposed solution offers managers from micro, small, and medium-sized enterprises analytical and information functions. Consequently, an evaluation method based on a scorecard framework and oriented toward BI&A systems and projects was presented by Dyczkowski, Korczak, and Dudycz (2014) to evaluate the decision support system applied in the InKoM project.

Table 2. Research topics of this study

Research Topic	Issues	Reference Articles
BI&A components	Data warehouse and reference models	Sharma et al. (2012), Pighin and Marzona (2012), Grabova et al. (2010), Olaru and Vincini (2014), Schuetz et al. (2016), Schütz and Schrefl (2014)
	KPIs	Schuetz et al. (2016)
	OLAP	Grabova et al. (2010)
	Data mining	Cheung and Li (2012), Kitayama et al. (2002)
	Dashboard	Korczak et al. (2012), Dyczkowski et al. (2014)
BI&A solutions		Grabova et al. (2010), Bernardino (2013), Lapa et al. (2014), Tutunea and Rus (2012), Olszak and Ziemba (2012), Nyblom et al. (2012), Gheorghe and Tonis (2015), M.K. Khan et al. (2014), Emam (2013)
Mobile BI&A		Dubravac and Bevanda (2015), Talati et al. (2012), Motta et al. (2014), Adeyelure et al. (2017)
Cloud BI&A	SaaS frameworks, architecture, and models	Hiziroglu and Cebeci (2013), Gash et al. (2011), Muriithi and Kotzé (2013), Liyang et al. (2011), Rostek et al. (2012), Fu (2008), S. Khan et al. (2011), Sheikh (2011)
	SaaS prototype	Hassanien and Elragal (2014)
	Critical success factors	Agostino et al. (2013), Emam (2013)
	Other issues	Kazeli (2014), Deepak et al. (2012), Rozehnal and Tvrdikova (2012), Moyo and Loock (2016)
BI&A application		Tyrychtr et al. (2015), Srichai and ThammaKo (2011), Papachristodoulou et al. (2017), Denić (2015)
BI&A adoption	Frameworks, maturity levels, determinants, and models	Boonsiritomachai et al. (2014), Boonsiritomachai et al. (2016), Qushem et al. (2017a), Puklavec et al. (2014), Puklavec et al. (2017), Chichti et al. (2016), Hatta et al. (2015), Gibson and Arnott (2003)
	Other issues	Gudfinnsson and Strand (2017), Hill and Scott (2004), Scholz et al. (2010), Qushem et al. (2017b), Sadok and Lesca (2009).
BI&A implementation	Critical success factors	Olszak and Ziemba (2012), Qushem et al. (2017b), Emam (2013), Sathiyam and Hiremath (2012).
	Frameworks, development cycles, models, and architecture	Guarda et al. (2013), Raymond (2003), Haque and Lutzer (2011), Sadok and Lesca (2009), Mahmoud et al. (2012)
	Prototypes	Neyoy et al. (2017), Bajo et al. (2012), Campos et al. (2007), Baransel and Baransel (2012), Wu et al. (2016), Devi and Priya (2016), Arrieta et al. (2004), M.K. Khan et al. (2014), Lee et al. (2009), Korczak et al. (2016), Dudycz and Korczak (2016), Shen and Ding (2008)
	Antecedents	Ali et al. (2018)
	Other issues	Horakova and Skalska (2013), Bergeron (2000), Raj et al. (2016), Gil and Sousa (2010)
BI&A benefits		Hočevar and Jaklič (2008), Lueg and Lu (2013), Gauzelin and Bentz (2017), Hariharan and Thangavel (2016), Scholz et al. (2010)

BI&A Solutions

The industrial use of open source BI&A has become increasingly common. Talend Open Studio, Mondrian Pentaho, and Palo are some of the web-based open source complete solutions that include extract-transform-load and OLAP and are suitable for SMEs, according to Grabova et al. (2010). Similarly, Bernardino (2013) analyzed seven of the most frequently used open source BI&A tools: Actuate, Jaspersoft, Palo, OpenI, Pentaho, SpagoBI, and Vanilla. These tools were tested using available public demos and are considered to be a mature set of open source solutions for BI&A. Lapa, Bernardino, and Figueiredo (2014) comparatively analyzed the above-mentioned tools to assist with the selection of BI&A platforms, and identified the most suitable solutions for SMEs. In addition, they presented the tools' architecture.

Only a few papers discussed other BI&A solutions for SMEs. Tutunea and Rus (2012) identified BI&A solutions for SMEs in the global market and in the Romanian market. They found that all BI&A solutions have modular functionalities that include dashboards, visualization, what-if analyses, interactive reports, and the easy sharing and distribution of information to users. Additionally, Olszak and Ziemba (2012) identified known BI&A systems in the Polish market including Comarch OPTIMA, SAP BusinessObjects Edge Edition, TETA Business Intelligence, Atlas, Express BI, and Oracle Business Intelligence Standard Edition One.

Other BI&A issues have also been presented in literature. Nyblom, Behrami, Nikkilä, and Søilen (2012) proposed a simple model for a BI&A solution performance evaluation based on the case studies of eight Swedish SMEs. These SMEs found efficiency, user friendliness, overall satisfaction, price, and adaptability to be most important. Gheorghe and Tonis (2015) presented BI&A solutions that could be adopted in Romanian SMEs. Moreover, M. K. Khan, Sohail, Aamir, Chowdhry, and Hyder (2014) and Emam (2013) presented a comparison of BI&A tools.

Mobile BI&A

Mobile BI&A provides access to information regardless of location and time to gain business insights through information analysis using mobile technology (Dubravac & Bevanda, 2015). Mobile BI&A is an excellent example of aligning IT strategies with enterprise strategies to attain a competitive advantage over its competitors (Stipić & Bronzin, 2011). Dubravac and Bevanda (2015) explored the adoption of Mobile BI&A in 83 SMEs in Croatia. They found that the importance and benefits of Mobile BI&A are not recognized in SMEs. The results indicated budget constraints and the knowledge of executives and users as two of the most significant barriers in Mobile BI&A adoption.

Other issues have been discussed in the Mobile BI&A literature. Talati, McRobbie, and Watt (2012) presented a model and system architecture for BI&A using mobile technology and the application program interface open source software. This architecture makes it possible for SMEs to be served with the power of BI&A at low cost. Similarly, Motta, Ma, You, and Sacco (2014) conducted a case study to illustrate the implementation of Mobile BI&A in a medium-sized enterprise. The proposed solution provided a reference model for Mobile BI&A based on low-cost open source technologies. The benefits of Mobile BI&A in SMEs were also presented in this study. Furthermore, Adeyelure, Kalema, and Bwalya (2017) proposed a Mobile BI&A framework for SMEs in developing countries. Their study also highlighted that organizational factors, environmental factors, technological complexity, technological compatibilities, relative advantages, vendor factors, entrepreneurial competencies, security factors, and infusion are pertinent in the deployment of Mobile BI&A in the SMEs of developing countries.

Cloud BI&A

Cloud computing and BI&A are becoming more important in achieving and maintaining a competitive edge (Ouf & Nasr, 2011). Cloud BI&A provides several advantages to small companies, such as lower implementation costs and greater ease of use (Horakova & Skalska, 2013). Therefore, Cloud BI&A is one of the BI&A trends expected to become popular among small companies.

Studies have discussed Cloud BI&A and Software-as-a-Service Business Intelligence (SaaS BI) in SMEs by proposing frameworks, such as conceptual frameworks for cloud-based open platform analytics (Hiziroglu & Cebeci, 2013), theoretical frameworks for Cloud BI&A (Gash, Ariyachandra, & Frolick, 2011), and frameworks for consolidated Cloud BI&A (Muriithi & Kotzé, 2013). Similarly, Liyang, Zhiwei, Zhangjun, and Li (2011) proposed a unified five-layer conceptual framework that includes infrastructure, data services, business services, user interface services, and operational services layers. Rostek, Wiśniewski, and Kucharska (2012) introduced the concept of Cloud BI&A for SMEs and considered the opportunities and risks of Cloud BI&A implementation.

Other authors presented the application architecture for BI&A (Fu, 2008) and proposed a model for Cloud BI&A to address the problems associated with traditional BI&A (S. Khan, Zhang, Khan, & Chen, 2011; Sheikh, 2011). Moreover, Hassanien and Elragal (2014) developed a novel approach by using tokenization as a mechanism for addressing security issues in Cloud BI&A. Their results showed that tokenization could largely replace traditional encryption techniques for securing BI&A data in the cloud.

Other BI&A cloud-related issues have been discussed in the literature. Agostino, Søilen, and Gerritsen (2013) conducted 36 interviews and identified a number of critical success factors (CSFs) in cloud-based BI&A. Their findings suggested that the most important CSFs are software functionality levels, ubiquitous access to data, responsive answers to customer support requests, handling of large amounts of data, and implementation costs. Similarly, Emam (2013) proposed a CSF model for implementing BI&A in the cloud. Emam argued that Cloud BI&A should be scalable and fixable to meet the continuous improvements of the solution. Kazeli (2014) described the concept of Cloud BI&A and addressed its benefits, problems, and challenges. Deepak, Deshpande, and Murthy (2012) proposed a pre-packaged configurable workflow for providing BI&A as a service on the cloud to SMEs in developing regions. They argued that the proposed workflow could help to improve market penetration for retail businesses in India. Similarly, Rozehnal and Tvrdikova (2012) studied the applicability of the BI&A SaaS model in Czech SME segments and presented its advantages. Furthermore, Moyo and Loock (2016) reported on the challenges that prevent SMEs in South Africa from adopting and using various Cloud BI&A solutions. The results indicated that security threats and vulnerabilities in various cloud deployments and services, as well as a mistrust of cloud service providers, are the main challenges in Cloud BI&A.

BI&A Application

BI&A has permeated various industries, such as retail, insurance, banking, finance and security, telecommunications, and manufacturing (Olszak & Ziemba, 2006). However, few studies have been conducted on the ways in which BI&A can be applied to different industries. Tyrychtr, Ulman, and Vostrovský (2015) examined the relationships between 135 agricultural enterprise structures and the use of BI&A in the Czech Republic. They found that only a few respondents used any type of BI&A application, although the results also suggested a high probability for the potential future use of BI&A among the respondents. The researchers also evaluated how BI&A could be applied to agricultural enterprises to assist in strengthening their production potentials and technical efficiencies. Similarly, Srichai and ThammaKo (2011) presented four dimensions that influence BI&A usage in Thai SMEs: human capital, knowledge processing, infrastructure, and culture. The researchers applied the technology acceptance model to explain the utilization of BI&A. Papachristodoulou, Koutsaki, and Kirkos (2017) presented the problems in and the advantages of the development and application of BI&A. Furthermore, Denić, Stevanović, Milićević, and Goran (2015) conducted a survey exploring the application of BI&A in Serbian SMEs.

BI&A Adoption

In an attempt to better understand BI&A adoption, a number of studies presented frameworks, maturity levels, models, and adoption theories. Other studies identified the challenges, factors, and determinants affecting BI&A adoption in SMEs. Boonsiritomachai, McGrath, and Burgess (2014) proposed a conceptual framework for identifying the current state of BI&A adoption in Thailand and the factors affecting the adoption of BI&A in SMEs. The same authors continued their study by proposing a BI&A maturity level concept that distinguishes different maturity levels for BI&A and identifying the factors affecting BI&A adoption in Thai SMEs (Boonsiritomachai et al., 2016). Qushem, Zeki, and Abubakar (2017) identified the determinants of BI&A adoption that lead to a better understanding of the development and testing of the BI&A framework. Similarly, Puklavec, Oliveira, and Popovic (2014) conducted semi-structured interviews with six BI&A experts and four adopters to identify the determinants that would serve as guides through the development and testing of BI&A adoption frameworks. A recent study by the same individuals conducted a survey using 181 SMEs to explore how technological, organizational, and environmental factors affect the individual adoption stages of BI&A (Puklavec, Oliveira, & Popovič, 2017). A technology, organization, and environment (TOE) framework and the IT adoption literature were used to develop the research hypotheses and a conceptual framework that explicates these relationships in a BI&A context. This study represents an important progress in theoretically understanding the role of technological, organizational, and environmental factors across different BI&A adoption stages. Chichti, Besbes, and Benzammel (2016) explored the determinants of BI&A adoption, which include technological, environmental, and organizational factors, in SMEs and Tunisian public organizations. Hatta et al. (2015) proposed a BI&A system adoption model for Malaysian SMEs and discussed two prominent adoption models used by SMEs: a diffusion of innovation theory and a TOE framework. Similarly, Gibson and Arnott (2003) proposed a model of the characteristics affecting BI&A adoption in small businesses. The model was developed on the basis of academic and government research.

Few BI&A adoption-related issues have been discussed in literature. Gudfinnsson and Strand (2017) conducted an in-depth qualitative case study to explore the challenges faced by SMEs in adopting BI&A. Another qualitative study conducted by Hill and Scott (2004) on 11 small businesses based in Northern Ireland proposed a set of recommendations for a successful BI&A adoption. Additionally, Scholz et al. (2010) conducted an exploratory analysis to examine BI&A adoption in German SMEs to distinguish the underlying constructs related to the perception of BI&A benefits, challenges, and organizational factors. Qushem, Zeki, Abubakar, and Akleylek (2017) presented a BI&A adoption trend and found that BI&A adoption is closely related to information and communications technology tool utilization. Moreover, Sadok and Lesca (2009) conducted an empirical survey using 20 French companies and identified seven necessary acceptance conditions of the BI&A model. The authors proposed using the model to help set up an environmental intelligence system for SMEs.

BI&A Implementation

Several papers discussed BI&A implementation from different angles by presenting CSFs, frameworks, development cycles, models, architectures, platforms, prototypes, and antecedents. Olszak and Ziemba (2012) conducted in-depth interviews with 20 SMEs from Upper Silesia and determined the CSFs that are vital to the implementation of BI&A in SMEs. They discovered three perspectives on CSFs: organization, process, and technology. Similarly, Qushem, Zeki, Abubakar, et al. (2017) defined the technological factors, process factors, and organizational factors as CSFs of BI&A implementation. Moreover, Emam (2013) proposed a CSF model and a model orientation from the organization, process, technology, and quality perspectives. Sathiyam and Hiremath (2012) presented CSFs from a design perspective, namely, sustainability costs for business viability, micro-localization needs for human desirability, and infrastructure considerations for technical feasibility. The researchers argued that their insights were based on their experiences in designing BI&A for Indian SMEs.

Guarda, Santos, Pinto, Augusto, and Silva (2013) proposed a framework for BI&A implementation that could be an efficient method for validating the requirements of a BI&A project. The proposed framework consisted of four phases: planning, technology, intelligence, and dissemination. The goal was to develop a framework that exemplifies and clarifies the gap between theoretical knowledge and the practical use of BI&A. Raymond (2003) introduced a conceptual and operational framework that focuses on the competitiveness of SMEs and that could orient BI&A activities and projects. Haque and Lutzer (2011) presented a development in BI&A involving the identification of KPIs, data integration, data warehousing, data analysis, and reporting. In addition, they performed a real-world functional application to demonstrate the BI&A concepts. Sadok and Lesca (2009) proposed a specific BI&A model that is based on the mobilization of corporate tacit knowledge and informal information, aims to interpret anticipatory environmental information, and assists in strategic decision making. Mahmoud, Marx Gómez, Peters, Rezgui, and Solsbach (2012) introduced an enhanced BI&A architecture with a Semantic-enabled Enterprise Service-Oriented Architecture (SESOA). They argued that one of the main outcomes of merging BI&A concepts with a SESOA framework is that it could help BI&A become mainstream in SMEs.

Several authors implemented the BI&A systems discussed in the literature. Neyoy, Rodríguez, and Castro (2017) proposed a prototype of BI&A for an SME in the restaurant industry. This prototype generated many positive results, including an improved competitive advantage for the company. Bajo, Borrajo, De Paz, Corchado, and Pellicer (2012) conducted a study aimed at providing innovative web BI&A for the management of SMEs in Spain. They implemented a multi-agent system, and 22 SMEs from different sectors of the Spanish market participated in the experiment. The proposed solution contributed to detecting potentially risky situations and providing recommendations. Campos, Sousa, Pereira, Perestrelo, and Freitas (2007) presented the architecture and the user interface of a BI&A system called the Eagle System and introduced several principles of an effective BI&A design. Baransel and Baransel (2012) presented the architecture of their proposed BI&A solution called BilişimBI and highlighted some of the outstanding features of their solution that make it an attractive alternative to SMEs. Wu, Gao, Wang, Min, and Wei (2016) proposed a general reference architecture for high consumable business analytics to improve the consumability of the BI&A. They also designed and implemented a prototype based on this architecture. Devi and Priya (2016) developed a BI&A solution for Sriram Industries and Sriram Wire Products using open source technologies. Their solution enabled the users to view detailed information on the status of sales and invoice. Arrieta, Azkarate, and Aranguren (2004) implemented an advanced BI&A system methodology specifically tailored for SMEs in the machine-tool sector that produces non-serial products. Advanced BI&A leads to more strategic decisions on new products and technology in the configuration phase of the product life-cycle management frame, guaranteeing a reduction in both cost and time-to-market and improving product quality. M. K. Khan et al. (2014) proposed a web support system for BI&A that provides and validates automated data mapping and loading from user applications to a BI&A framework. The implementation of this system offers convenience of use and effective cost-saving. Lee, Lau, Ho, and Ho (2009) proposed the development of an agent-based procurement system to enhance BI&A and conducted a case study on a manufacturing SME to validate the feasibility of this approach.

Korczak, Dudycz, Nita, Oleksyk, and Kaźmierczak (2016) proposed an extended functionality and knowledge of BI&A to attain the managerial requirements in SMEs. They focused on two major aspects of the BI&A system: the interface that considers the manager's level of knowledge and the interface that supports the interpretation of economic and financial information using the built-in domain ontologies. Dudycz and Korczak (2016) presented the design and use of financial ontology to enhance BI&A. Shen and Ding (2008) presented a BI&A system design based on the application service provider platform to address the informatization issue in SMEs and enhance their competitiveness. Further, Ali, Miah, and Khan (2018) suggested several antecedents of BI&A implementation that had been recognized for having achieved organizational agility in small businesses. They found that organizational capability has largely been recognized as a key antecedent of BI&A implementation.

Other implementation-related issues have been discussed in literature. Horakova and Skalska (2013) introduced a BI&A implementation process for a small company and argued that the use of open source tools and applications could lead to a decrease in BI&A implementation. Bergeron (2000) further addressed this issue by analyzing BI&A implementation in SMEs and large enterprises as well as in the cultural sector and by arguing that BI&A requires a holistic approach. Raj et al. (2016) examined the challenges in BI&A implementation in an SME in the United Kingdom. They recommended the following ways in which SMEs could approach BI&A implementation: highlighting the need for a good understanding of the existing data source, cleansing and transforming the data, creating a data warehouse based on Kimball's approach for storing the transformed data, and presenting the data to end users using various visualization tools. Gil and Sousa (2010) developed a method for a successful BI&A implementation by using performance indicators based on business process monitoring and by constructing a plan of action to conduct a defined strategy using target objectives. They argued that the use of performance indicators based on business activities could lead to a critical path for strategy development.

BI&A Benefits

Several studies were conducted on the benefits of BI&A. These benefits include faster and easier access to information (Gangadharan & Swami, 2004), savings in IT infrastructure costs (Watson & Wixom, 2007), and greater customer satisfaction (Lönnqvist & Pirttimäki, 2006). However, few studies specifically discussed the BI&A benefits for SMEs. Hočevar and Jaklič (2008) assessed the potential benefits of a BI&A system called Melamin in an SME and argued that the first and most common purpose of benefit evaluation is to demonstrate that BI&A is worth the investment. Lueg and Lu (2013) revealed that standard BI&A solutions could help SMEs to increase their efficiency in budgeting within short time frames. They performed a case study on a Danish SME to demonstrate the most pressing problems in budgeting efficiency and found that affordable standard BI&A solutions could address these problems. Recently, Gauzelin and Bentz (2017) examined the influence of BI&A on organizational decision making and performance by conducting 200 interviews from 10 selected SMEs. Hariharan and Thangavel (2016) discussed the effectiveness of BI&A and argued that BI&A has become an important requirement for achieving competitiveness. Further, Scholz et al. (2010) presented additional important benefits of BI&A.

DISCUSSION AND FUTURE RESEARCH AVENUES

This study presented an overview of the publications on BI&A in SMEs through a systematic literature review of studies published between 2000 and 2018. In this review, 78 articles met the inclusion criteria, but 29 of them did not clearly define the specific research methods applied. This outcome is an indication of an immature research field, and thus more empirical research on BI&A is needed. The subsequent discussion presents the research gaps and future research avenues that address RQ2.

The various BI&A components presented can form different BI&A technologies and tools. In developing a BI&A system, a detailed understanding of these components can lead to a solid architecture design and successful implementation. According to Schuetz et al. (2016), many SMEs refrain from adopting BI&A technology, but reference models enable them to overcome the obstacles associated with the introduction of BI&A solutions. Several studies focused on the components of BI&A (Gupta & George, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2017), but they did not address the SME context. Therefore, further research should address the development of additional reference models for BI&A components in SMEs.

The mature set of BI&A open source solutions presented in this study addresses most areas of the BI&A functionality. Therefore, it has become a solid option for any organization, especially SMEs, to achieve and surpass their BI&A needs. The opportunities that open source BI&A can offer to SMEs and the types of decisions that can be made with certain tools can be a useful avenue for future research.

The upsurge in the mobility of information has yielded various enterprise ambitions of adopting mobile business inventiveness, and it is strengthened by such benefits as the facilitation of access to important information at any given location (Davenport, Harris, & Morison, 2010). Therefore, mobile phones have become an essential part of enterprises. The ability to ubiquitously access services on the move is truly remarkable. However, the following important aspects need further attention: cost; deployment methods; information display, interaction, and exploration; context awareness; offline mode exploration; rich application functionality; and multiple device support. Moreover, an explicit focus on leveraging mobile security capabilities, delivering secure authentication, supporting virtual private network and Hypertext Transfer Protocol Secure, and applying sandboxing to BI&A developers is vital. Therefore, more studies in this area can help to avoid user frustration and to promote BI&A adoption.

In addition to open source solutions, Cloud BI&A is also considered a low-cost, licensed alternative solution for SMEs. Although factors, frameworks, and models have been presented to address the successful implementation of Cloud BI&A in the literature, empirical studies have not discussed its benefits. Although the cloud is a good option, the reluctance of SMEs to enter the cloud because of security and control issues, particularly in ownership, remains an obstacle. Therefore, future studies should focus on these issues.

When used correctly, BI&A can deliver knowledge, efficiency, better and timelier decisions, and profit to almost any organization. As studies on BI&A application usually pertain to traditional manufacturing SMEs that employ it, research on BI&A application in other types of industries is also needed. These studies may yield different research findings and help to make BI&A more mainstream in SMEs.

Understanding the definition of BI&A, the reason one should apply it, and its corresponding benefits are significant in adopting BI&A across enterprises. Although some studies examined the determinants and theories of BI&A adoption, most did not extend the knowledge on the readiness of SMEs to establish BI&A. Such knowledge can be valuable for owners and senior management to become more proactive in promoting BI&A. More empirical studies on the determinants and barriers in BI&A adoption would be valuable.

Several frameworks and models have emerged that provide guidance in identifying the factors supporting the successful implementation of BI&A. However, there is no clear definition for success. In addition, BI&A initiatives with or without data warehouses have not been extensively studied relative to the realized benefits. Furthermore, the need for delivering significant return on investment has not yet been fully discussed and the total cost of ownership has not yet been minimized.

BI&A benefits are usually greater than initially thought. Similar to that in large organizations, the most sought-after outcome in using BI&A in SMEs is to make better decisions (Dresner, 2014). Surprisingly, few studies have focused on BI&A benefits within SMEs. According to Gibson et al. (2004), limited academic research has been performed on the benefit evaluations of BI&A. Therefore, further studies should assess and evaluate the benefits of BI&A.

More studies in this domain can improve the understanding of the value of BI&A and of how these systems can be utilized to create intelligence. In addition, capturing the value of BI&A can offer different perspectives as it requires SMEs to go beyond technical implementation. This result is consistent with that of Vidgen, Shaw, and Grant (2017), who proposed several challenge focal areas for creating business value: a clear data and analytics strategy, the right people to affect a data-driven cultural change, and the consideration of data and information ethics when using data for competitive advantage. Mikalef et al. (2017) emphasized the importance of understanding the different mechanisms and processes for creating BI&A business value. They also argued that in highly dynamic and turbulent environments, the companies that could reinforce their organizational capabilities through the targeted use of BI&A would likely gain competitive advantage.

BI&A has permeated various industries, such as manufacturing, banking, insurance, telecommunications, and retail (Olszak & Ziemba, 2006). However, BI&A technologies and applications in other industries (e.g., hospitality) are still at a nascent stage of development. To make BI&A more mainstream for SMEs, certain issues need further attention, for example, establishing standards and governance; safeguarding security; guaranteeing privacy, usability, and flexibility; and continually improving the technologies. Moreover, presenting empirical success and failure reports to understand the disparate capabilities of BI&A, assisting SMEs in circumventing common pitfalls during implementation periods, and facilitating the selection of BI&A solutions would be beneficial.

One issue not found in the literature is that of the General Data Protection Regulation (GDPR) of the EU. The GDPR was approved in April 2016 and reinforced in May 2018 (Europe Commission, 2018). The GDPR concerns the processing of personal data by individuals, companies, or organizations related to any individual in the EU. Therefore, people now have more control over their personal data, and businesses can benefit from a level playing field. Considering BI&A is all about making sense of the data and examining the effects of the GDPR on BI&A systems is interesting. These effects may lead to several research opportunities.

Figure 4 reveals the lack of field inquiry, descriptive, design, and interview method studies. Further investigations using these methods may yield a more in-depth understanding of BI&A in the SME context. As depicted in Figure 3, BI&A research has become more stable since 2011. The research topics highlighted above should be addressed to further advance BI&A knowledge. The identified research gaps and suggestions for future research directions can help to develop a better understanding of the phenomena studied so that the research field will progress. Table 3 summarizes the identified research gaps and suggestions for future research.

CONCLUSION

A systematic literature search was conducted to provide a comprehensive literature review of empirical studies on BI&A in SMEs. Most of the literature focused on proposing frameworks, architecture, models, critical success factors, determinants, antecedents, and barriers that influence BI&A implementation and adoption. The review provides promising evidence for practitioners and will help guide them when embarking on BI&A projects. For BI&A vendors, this literature can help them improve upon their BI&A solutions, for example, by offering improved usability, integration into other systems, and ease of deployment.

This study also identified research topics, gaps in the literature, and suggestions for future research in BI&A. More specifically, the BI&A literature was found to be lacking in studies that focus on (a) the purpose of BI&A components to assess SMEs' readiness for BI&A projects; (b) the benefits evaluation, assessment, and realization of BI&A; (c) factors such as return on investment, total cost of ownership, and security and privacy issues that influence BI&A adoption and implementation; (d) how BI&A are used for decision-making; and (e) different usage of BI&A in various business fields and industries. Further, cloud and mobile-based BI&A solutions are promising areas of application for SMEs.

This study suffers from some limitations. Although a thorough literature search was conducted, there is no guarantee that all the materials in this area have been addressed.

Table 3. Research gaps and future research avenues

Identified Research Gaps	Suggestions for Future Research
A lack of understanding of BI&A components and their importance when embarking on a BI project.	Further studies exploring the purpose of the BI&A components in assessing SME readiness for BI&A initiatives.
Few studies on how BI&A tools are used for decision-making.	Investigating the utilization of BI&A tools and exploring the types of decisions being made using them.
Very few issues that inhibit Mobile BI&A adoption are explored.	Exploring the influence of issues such as security, deployment costs, and ownership costs and further investigating enablers of Mobile BI&A adoption.
Limited investigation into the benefits and challenges that hinder Cloud BI&A.	Further study of the benefits of Cloud BI&A and issues such as security and cost.
A lack of diverse research regarding different types of industries applying BI&A.	Performing more research on various types of industries employing BI&A.
Few studies addressing BI&A adoption in developing countries.	Investigating best practices and case studies that prove the business value of BI&A in terms of decision-making and sustainable development in developed and developing countries.
A lack of research on different technologies and techniques that can extend the capabilities of traditional BI&A.	Expanding the selection of BI&A initiatives, e.g., implementing BI&A with or without data warehouses, the automated data warehouse approach, and machine learning.
Minimal evaluations of BI&A benefits.	Investigating how BI&A creates business value and the factors affecting the realization of benefits.
Few studies using field inquiry, descriptive, design, and interview research methods.	More studies using these methods to create a more in-depth understanding of the phenomena.

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Marilex Rea Llave is a PhD candidate in Information Systems at the University of Agder in Norway. Her research has a focus on business intelligence and analytics in small and medium-sized enterprises. She received her MSc in Information and Communication Technology (ICT) from the University of Agder and BSc in Computer Science from San Sebastian College-Recoletos de Cavite, Philippines. She also received the award for "Best Master's Thesis in ICT". Her main research interests include: business intelligence, business analytics, big data, data science, and machine learning.

Creating Value from Business Intelligence and Analytics in SMEs: Insights from Experts

Completed Research

Marilex Rea Llave
University of Agder, Norway
marilex.r.llave@uia.no

Eli Hustad
University of Agder, Norway
eli.hustad@uia.no

Dag H. Olsen
University of Agder, Norway
dag.h.olsen@uia.no

Abstract

This paper reports from an exploratory study that examines utilization of Business Intelligence and Analytics (BI&A) in Small-and-Medium-sized Enterprises (SMEs). In total, 24 semi-structured interviews of BI&A experts were conducted. The experts highlighted several critical issues that SMEs should consider: (1) to "start Small, think Big" was emphasized as an appropriate BI&A investment strategy for SMEs to obtain value in terms of both "quick wins" and long-term assets and impacts, (2) to consider BI&A investment without implementing a traditional data warehouse, and (3) to consider the automated data warehouse approach. In addition, the experts underscored to pay more attention to data governance. A recognized value framework from the literature was applied as an analytical lens to interpret the findings. We suggest modification of this framework to make it less "waterfall" oriented and more iterative and agile to create value from BI&A in SMEs. Future research should assess SMEs' readiness and capabilities for BI&A. In addition, we need to understand the exclusive needs for decision-making in SMEs across industries.

Keywords

Business intelligence and analytics, SMEs, BI&A value framework, data governance.

Introduction

For several decades, scholars and practitioners alike have been paying attention to how business intelligence and analytics (BI&A) approaches in enterprises can improve decision-making processes and create business value. BI&A systems are important for visualizing and understanding enterprises' data to support their management teams in extracting and utilizing core information resources in more intelligent ways (Guarda et al. 2013). BI&A systems are considered vital tools for improving internal business processes and for gaining effective reporting, and externally, they are important as market predictors for strengthening a sustainable, competitive position in the marketplace (Gilad and Gilad 1988).

While tools for efficient decision-making have been highly attractive to larger companies for some time, small and medium-sized enterprises (SMEs) have recently started to notice and take advantage of BI&A approaches that are suitable for their needs (Scholz et al. 2010). However, the research on BI&A in SMEs is limited because most of these systems are implemented in larger enterprises, and previous empirical research has mostly been conducted in that context (Llave 2017).

SMEs differ from larger enterprises in several ways; normally, SMEs have limited internal information technology (IT) resources and competencies available, and they are dependent upon external expertise when starting new IT projects, such as acquiring and implementing new business intelligence (BI) applications. The primary goal of BI is to enable the use of information, and an important aspect of BI projects is turning data into usable information (Larson and Chang 2016). SMEs may have different needs regarding the types of decisions that need to be supported compared to larger companies, and it is important to understand how SMEs can utilize BI&A to take advantage of their information in more intelligent ways. They may also have limited financial resources for investing in BI&A, so it is likely that they consider different investment strategies. Therefore, more empirical research is needed to understand how SMEs can utilize BI&A to become more efficient in turning their data into usable information and to foster analyses that can improve their decision processes to generate value at operational, managerial, and strategic levels. This has been an important issue for larger enterprises in the decision support system literature (Arnott et al. 2017).

SMEs play a significant role in the economy of most countries and constitute important sources for economic development (Olszak and Ziemba 2008). Moreover, SMEs are the focal point in shaping enterprise policy in the European Union (EU). The EU considers SMEs to be the key to ensuring economic growth, innovation, job creation, and social integration (Airaksinen et al. 2015). Therefore, more research on SMEs is essential.

To bridge this research gap, we performed an exploratory study comprising 24 interviews of BI&A experts from user organizations and vendors of BI&A solutions. We were then able to build a rich picture of how SMEs tackle the implementation and utilization of BI&A solutions across different industries. The study focused on how BI&A is applied to improve SMEs' business processes and how SMEs can ensure that their investments in BI&A will deliver business value. By doing so, we hoped to gain valuable insight into the factors that can influence BI&A adoption in SMEs, fill the gaps in the literature, and facilitate the progression of BI&A research on SMEs.

Our inquiry offers two important contributions. First, this research empirically identified the significant issues that SMEs need to consider when investing in BI&A. Second, we applied well-known value frameworks from the literature that utilize process theory to understand how SMEs may create business value when implementing BI&A systems (Soh and Markus 1995; Trieu 2017). By utilizing this framework as an analytical lens to understand BI&A processes in an SME context, we recommend introducing a more agile and incremental approach into this framework to better meet the needs of SMEs. The paper is organized as follows. First, we present the background for this research and the foundation for the development of the research questions. Second, we provide a description of our research method. Then we present our results, followed by discussion, implications, and our conclusion.

Background and Development of Research Question

BI is defined as a "broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions" (Wixom and Watson 2012). As the terminology of BI has evolved, the term *business analytics* has also been used to describe applications that provide decision support (Davenport 2006). Thus, business intelligence and analytics (BI&A) was proposed as a unified concept and term for describing information-intensive concepts and methods for improving business decision-making (Chen et al. 2012). BI&A systems are complemented by specialized IT infrastructures, which include data warehouses and data marts, as well as extract, transform, and load (ETL) tools (Ong et al. 2011).

We have adapted Trieu's framework as an analytical lens to explore how BI&A creates business value in SMEs (Trieu 2017). Trieu's work incorporates several acknowledged frameworks from the IS literature that utilize a process theory approach (Melville et al. 2004; Schryen 2013; Soh and Markus 1995). Figure 1 illustrates the value framework that links BI&A investments to organizational performance through certain steps. This is demonstrated as a chain of necessary conditions. For example, to increase organizational performance, the enterprise needs to obtain a certain degree of BI&A impacts, which in turn requires BI&A assets to be generated from BI&A investments. A process approach is beneficial to understanding how SMEs manage BI&A investments that yield BI&A assets, which again impact organizational performance over time. In addition, a process approach seeks to understand the underlying and interrelated probabilistic processes that are most appropriate for explaining uncertain outcomes in the research on IT investment and business value compared to variance models.

First, the link between BI&A investments and BI&A assets involves the conversion process. According to the literature, BI&A investments induce better business performance and are necessary but are not a sufficient condition for BI&A assets. The four areas that are strongly associated with BI&A conversion activities include formulating BI&A strategies, selecting appropriate organizational structures for BI&A

strategies, selecting the right BI&A projects, and managing BI&A projects effectively. The non-BI&A investment strategies include risk management (Benaroch et al. 2007) and investments in the practice of sales and operation planning (Trkman et al. 2010).

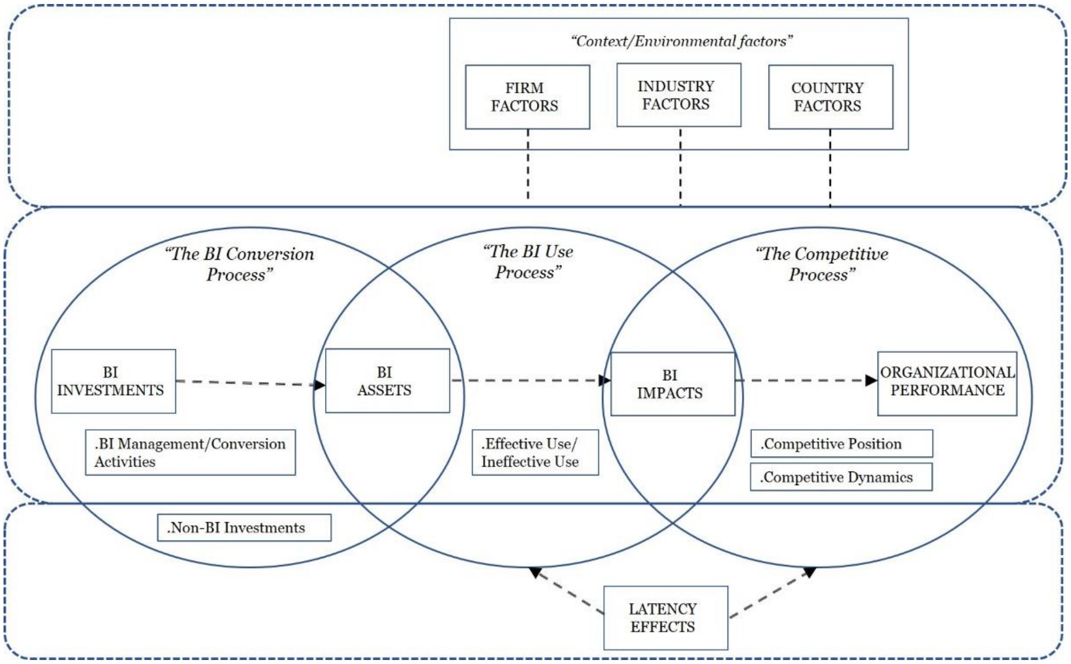

Figure 1. A Framework of How BI Creates Value (Trieu 2017)

BI&A investments consist of BI&A-related hardware, software, technical infrastructure, human resources, and management capabilities (Schryen 2013). At this stage, SMEs need to make appropriate investment selections based on their actual needs for support in decision-making processes. This also depends upon the financial situation of the SME in question and the solution it prefers. For many SMEs, cloud solutions can be good investments at low costs. The conversion process from investments to assets highly depends upon the IT maturity of the SME, the human resources available, and the application portfolios they have installed. Since BI&A constitutes a quite distinct IT investment, the companies need to have knowledge about which data they want to use, which decisions they should get support for, and how to turn data into valuable information. Moreover, good data collection strategies are essential for making BI&A assets. This involves focusing on data governance in terms of improving data quality and removing data inconsistencies (Ramakrishnan et al. 2012). We would expect that a focus on data governance will be important for SMEs in the process of creating BI&A assets.

Second, the link from BI&A assets to BI&A impacts depends on the effective use of BI&A. High-quality BI&A assets are a necessary—but not sufficient—condition for achieving BI&A impacts. Moreover, processes such as system development cycle time, business operations productivity, and BI&A planning can reduce effectiveness and result in negative impacts. *BI&A impacts* refers to a state in which enterprises have achieved one or more of the following outcomes: improved operational efficiency of processes, new/improved products or services, and/or strengthened organizational intelligence and dynamic organizational structure (Melville et al. 2004; Soh and Markus 1995). Moreover, a positive decision-making culture in the organization can play an important role in generating BI&A impacts when it builds upon deeply analytical evidence-based decision-making (Elbashir et al. 2008).

In addition, firm, industry, and country factors (as well latency effects) are important because they affect the success of the conversion of quality BI&A assets into BI&A impacts (Trieu 2017). Previous research has documented that BI&A systems provide different values depending on the types of industry in which an enterprise operates (Elbashir et al. 2008; Rouibah and Ould-ali 2002). BI&A has permeated various industries, such as retail, insurance, banking, finance, telecommunications, and manufacturing (Olszak and Ziemba 2006). For SMEs, it is likely that various industries will have different needs for decision support.

We would expect that the need for BI&A varies across industries, so a diversity of BI&A investments is likely to be utilized.

Finally, the link from BI&A impacts to organizational performance depends on the competitive process. Organizational performance includes measures of successful goal accomplishment, satisfaction of constituents, and the ability to obtain valued inputs from scarce resources. BI&A impacts are important and necessary but are not sufficient to result in improved organizational performance. The necessary conditions and probabilistic factors crucial to improving organizational performance include the competitive position of an organization, competitive dynamics, industry and country factors, and latency effects. Furthermore, obtaining BI&A impacts is the first necessary condition for improving a company's organizational performance (Elbashir et al. 2008).

Building on Trieu's framework, we are interested in exploring the different activities that SMEs undertake when they start the BI&A conversion process and move through the BI&A use process and finally into the competitive process (Figure 1). Thus, our overarching research question is as follows: *How are SMEs creating value from BI&A systems?*

Research Method

In this exploratory study, the expert interview technique was used (Meuser and Nagel 2009). The data collection comprised 24 semi-structured interviews with BI&A experts from various industries in Norway. The BI&A experts were identified using LinkedIn to find appropriate informants that had various BI&A roles. In addition, we used a snowballing technique in which we asked each informant to suggest other people we could talk to. An overview of the informants' roles is presented in Table 1.

At the beginning of each interview, the BI&A experts were asked to give brief information about how they currently work with BI&A. Also, we gave them a brief description of the status of BI&A adoption in SMEs according to the literature. The focus of the interviews varied depending on the interviewees' professions. In addition, each BI&A expert was informed about the main goal of the study, which was to explore BI&A adoption in Norwegian SMEs.

Role	Industry	Role	Industry	Role	Industry
Consultant	IT Consultancy	BI User	Chemicals	Data Scientist	BI Software Provider
Consultant	Oil & Gas	Head of BI	IT Consultancy	Data Scientist	Insurance
Consultant	IT Consultancy	Head of BI	Chemicals	Data Scientist	IT Consultancy
Consultant	IT Consultancy	Head of BI	IT Consultancy	Data Scientist	IT Consultancy
Consultant	IT Consultancy	Head of BI	Insurance	Data Scientist	Banking
Advisor	IT Consultancy	Head of BI	IT Consultancy	Vendor	BI Software Provider
Advisor	Investment Consulting	Head of BI	Banking	Vendor	Consulting & Advisory Services
BI User	Food & Beverages	Head of BI	BI Consulting	Data Governance Leader	Insurance

Table 1. The Informants' Roles and Industry Domains

The data analysis was performed using thematic analysis (Braun and Clarke 2006). First, all the interviews were transcribed and analyzed using NVivo. Then we performed the first phase, which was to become familiarized with the data. In this phase, we read and reread the transcripts and noted some initial ideas. Second, we coded the interesting features of the data in a systematic fashion and collated the data that were relevant to each code. Third, we searched for potential themes and reviewed each of them. Fourth, we generated clear definitions and names for each theme. Finally, we produced a report on the analysis, which is presented in the results section.

Results

We present the results from the expert interviews in this section. First, we address the BI&A conversion process in the SMEs. We then look at the BI&A use processes in various industries and present the competitive process.

BI&A Conversion Process

The informants emphasized three BI&A investment issues in particular: the need for an iterative and gradual investment strategy, whether the BI&A should be built without a data warehouse, and whether the BI&A system should be implemented with an automated data warehouse. In addition, they highlighted the importance of data governance.

First, a majority of the informants emphasized the importance of an iterative and gradual approach to the investment and building of the BI&A asset. Several informants used the expression "start small, think big" to denote this investment strategy. For example, one informant explained that "When enterprises embark on a BI&A project, it is important to think big, but to start very small." The informants expressed that it is crucial to focus on the things that are easy to deliver, based on what is known about the data quality and the resources available for the project. Therefore, it is better to do small deliveries, scoping and narrowing down to small areas that will give quick wins to the business. This contributes to building the legitimacy of further BI&A investments and making the BI&A effort business driven. The following quote is illustrative of this logic: "when you deliver something that is giving value to the organization, it will be much easier to move on, to continue the investment and take initiative to build the whole picture [...] It is important to have the big picture as a guideline, but you still deliver solutions that are manageable in a small amount of time." The informants believed that it is necessary to start small but to have a complete vision of the future BI&A asset and its functionality and contribution to value creation. One of the informants noted that "From the end of the 1990s until the beginning of the millennium in Norway, when a company launched a BI&A initiative, they always covered everything." Back then, it was normal to start building a data warehouse without knowing the needs of the users.

Several of the informants also pointed out that a BI&A system should be dynamic and evolve over time. Most businesses change quite frequently; new products and services are created, and new data sources become available, meaning that new systems may need to be interfaced, such as applications in the Cloud. According to these experts, BI&A systems need to be agile to deal with these changes. There will be iterative adjustments during the lifecycle of the system.

Second, several of the informants from BI&A vendors noted that SMEs should consider adopting BI&A without a data warehouse. They had SME clients from a wide range of industries. These enterprises have adopted BI&A technologies such as PowerBI, Tableau, and QlikView. These BI&A assets are pre-built solutions, so the clients do not have to worry about the technology aspect. One of the informants noted that "when enterprises are content with the tool and see what [the tools] can deliver, then [the enterprises] come back to us and we expand the use of the tools." In addition, several informants stated that getting the data from the source systems and modeling it in a star schema can be done in spreadsheets like Excel as well. The informants also noted that Excel is very easy to use out of the box and that it can be appropriate for small enterprises that only have few data sources and only need a few reports. They further asserted that it is sometimes possible to connect Excel to the data source systems and use Excel as the "local data warehouse," or the data source for the reporting tool. One informant stated that "depending on how much data you have, it is not necessary to have a huge server." In addition, several of the informants acknowledged that building a data warehouse can be a very expensive investment for an SME. In addition, the return of investment, delivery point, and delivery time can be very tough to quantify. Several of informants argued, therefore, that it may not be necessary to have all the data in one place and that the thing that matters most is that the users can have immediate access to the data and do their analyses. This indicates that a small portion of data with the right BI&A assets may be sufficient. Further, most of the informants acknowledged that "BI&A investment is beneficial for any type of business."

Third, the informants also emphasized that employing an automated data warehouse could be a feasible option for SMEs. Several of the informants illustrated how innovative BI&A technologies can automate some of the processes in building a data warehouse. These technologies are designed to automate and improve all aspects of data warehousing. They noted that this approach is faster and cheaper compared to the traditional data warehouses, which are complex, costly, and time consuming. Two of the informants pointed out that automated data warehousing automates the ETL processes, which normally account for more than 80% of a BI&A project, while 20% of the effort is spend on reports and analytics. One of the informants from a BI&A vendor stated that "automated data warehousing is [optimizing] the process of getting the data prepared and ready for reporting [...] but not at the cost of quality, governance and documentation [...] And in automated data warehousing, we try to switch to twenty percent for preparation of data and eighty percent for decision-making processes." He also noted that "most of our customers come to us because they have multiple versions of business rules, and everything is kind of messed up, and they have no documentation [...] And yes, data warehousing is really expensive and takes a lot of time, but if you have a way to do this faster and cheaper, you kind of have to do it."

In addition, several of the informants pointed out that data governance is a neglected issue in BI&A implementation. This is illustrated by the following quote from one informant: "In the 1990s and at the beginning of the millennium, the people who built data warehouses were also the ones who were responsible for data governance [...] It was wrong, and this was one of the main reasons why the success rate of BI initiatives was very low." He underscored that "Data Governance is a business matter, not an IT matter. Data warehouse developers are usually IT-resources and has a technical mindset. That also means they treat data issues as technical issues instead of challenging the business processes - both the business processes that creates the data and the ones that use the data and defines their requirements. When the business side looks upon data management as an IT matter, they don't realize a part of the data quality problem and do not do their part in improving data quality". In addition, one of the informants noted that "I would say that in ninety percent of all cases, when you start a data warehouse project, that you kind of come to the point where, okay we need to start over again [...] And the reason for that is data governance; you need someone to tell you how to use the data, you need a strong governance in your data." The informants explained that data governance means having control over the data's availability, usability, integrity, and security. One of the informants from the banking sector emphasized that it is important to have data governance as an independent enterprise function that guides decision-making regarding the creation, use, and disposition of business information. She stated that "a data governance leader is responsible for implementing the decision rights and support mechanisms to ensure that the trust, accuracy, consistency, accessibility, and security of information across the enterprise are maintained"—hence the business need to have an enterprise-wide definition of *data*. Further, these informants noted that implementing a data governance framework is not easy.

BI&A Use Process

The interviews revealed that the use of BI&A was perceived to be important in gaining control over data. All of the informants emphasized the use of BI&A for making better and more informed decisions, because BI&A provides facts to support decision processes through the collection, processing, and presentation of data. These are decisions that are based on facts rather than gut feelings. Most of the informants believed that when an enterprise has trouble making informed decisions due to the amount and complexity of its data, then BI&A would make sense. The informants explained how SMEs use BI&A assets to achieve BI&A impacts. The interviews indicated that one of the major reasons for adopting BI&A assets in SMEs is automation. BI&A tools are used to automate their existing reporting and to avoid other tedious tasks, such as copying, pasting, uploading, and downloading the data. Therefore, automation became one of the selling points for enterprises that are unfamiliar with the full capabilities of BI&A. In addition, some of the most mature SMEs are using BI&A to automate decision-making.

The informants pointed out the contextual differences of BI&A usage in various sectors and emphasized the financial sector. All of the informants pointed out that banks have always been data-driven. They use BI&A for reporting and to make informed decisions, since banks licensed in Norway have a strict reporting obligation to the Norwegian authorities. The authorities impose a violation penalty when banks fail to meet the reporting deadlines. Therefore, BI&A is an important tool in handling this reporting issue. Banks are also using BI&A for automated decision-making, for instance in granting loan processes. This process collects information about the customer who applies for a loan. BI&A is used to automate all of the processes of collecting the information and all the way through to making the decision. Insurance companies are also using BI&A to have full control over their data, for instance, when dealing with insurance claims and reservation processes for future damage. Moreover, most informants firmly believed that banks and insurances companies were the early adopters of BI&A.

Several of the informants talked about how production SMEs use BI&A. BI&A are used to automate their reporting and to track orders throughout production, as well as to enable informed decision-making in staffing, ensuring correct pricing, and planning production. Similarly, the interviews revealed the use of BI&A for automated reporting in architectural and private equity companies. Many informants noted that sales companies are also using BI&A to track sales for every product group and for handling bonus systems for the sales clerks. Restaurants are using BI&A to generate reports that show when their staff is working and when sales are made. As a result, they have full control over how the general sales are evolving. They also use BI&A to make informed staffing decisions and enable management to react with greater speed.

The informants perceived four BI&A impacts to be particularly significant: business insight, customer insight, cost reduction, and competitive advantage. Gaining business insight was considered the most important BI&A impact. Most of the informants agreed that to have business insight is to know how the business is doing, its strengths and weaknesses, its place in the market, and its competitors. Most of the informants firmly believed that BI&A assets can lead to competitive advantage when they have become the core of the businesses' knowledge. Many of the informants believed that any enterprises that are implementing and using BI&A assets in the right way will achieve BI&A impacts.

The informants considered customer insight to be an important BI&A impact. Many of the informants noted that customer insight can increase sales and improve customer retention. One of the informants noted that "with BI&A, enterprises can know which customers are highly valuable, which are valuable, which are less valuable, and which are not valuable." Customer retention means reducing the churn rate and improving customer loyalty. Several informants also mentioned customer segmentation and that having consumer insight can help enterprises to focus on the right customers, identify customers with high churn probability, and initiate specific retention activities. With BI&A, enterprises can create intelligent campaign management using their customer data to select target groups for upselling and cross-selling.

The informants also pointed to cost reduction. Several of the informants talked about how automated reporting can lead to cost reduction by saving time. They stated that "BI&A reduces the time spent by CFOs in making financial reports for the board of directors [...] Then CFOs will have more time to analyze the data." Similarly, many informants mentioned that automated decision-making provides further cost reduction. For instance, loan-granting processes in banks can be performed without any human involvement. Some informants also noted that BI&A can help production companies better optimize their use of resources, like raw materials.

Competitive Process

As mentioned earlier, BI&A impacts are important and necessary but not sufficient to result in improved organizational performance. According to the literature, competitive position and competitive dynamics are some of the factors that can help enterprises to convert favorable BI&A impacts into organizational performance improvement (Trieu 2017). The interviews revealed that the informants had little focus on this process. Their main focus was on the conversion and use processes and, in particular, realizing short-term BI&A impacts and benefits, but they implicitly acknowledged the importance of eventually achieving improved organizational performance.

Discussion and Future Research

In this section, we discuss the most important findings. We saw that the informants emphasized three issues in particular: an iterative and gradual investment strategy, whether the BI&A should be built without a data warehouse, and whether the BI&A system should be implemented with an automated data warehouse.

First, the informants believed that an iterative and gradual investment strategy was preferable for SMEs. This implies that they should address simple-use cases first and realize benefits from them before iteratively adding more extensive functionality. For each iteration, they should realize the benefits before defining the next iteration. This perspective goes beyond an incremental delivery approach, as described by Yeoh and Popovič (2016) and García and Pinzón (2017). It is also about creating the initial success stories and organizational learning that will be important for future BI&A investment decisions. We contend that such early success stories are crucial for creating legitimacy for the BI&A project and for overcoming organizational skepticism towards it. Therefore, it is vital in order to secure resources for the further BI&A investments. We also contend that it will help secure a strong business grounding for the BI&A project and, thus, ensure that it is business driven. In addition, we saw that several of the informants emphasized that BI&A systems need to be agile and evolve with the business. In this regard, the systems should never be perceived as complete, and the BI&A effort should last for the entire system lifecycle.

The BI&A value framework in Figure 1 illustrates the BI&A value creation process as a set of sequential stages, where each is more or less completed before progressing to the next stage. BI&A investments are converted into BI&A assets, which, through the use process, lead to BI&A impacts, which, through the competitive process, lead to organizational performance. There are no iterations in this framework, so we argue that it fails to illustrate that BI&A assets need to be dynamic and constantly evolving. This is unfortunate, as it influences how we perceive BI&A efforts, as linear "water-fall" projects. We propose that we need to modify this framework to represent the iterative and dynamic nature of BI&A. Figure 2 depicts how the framework can be revised with feedback loops.

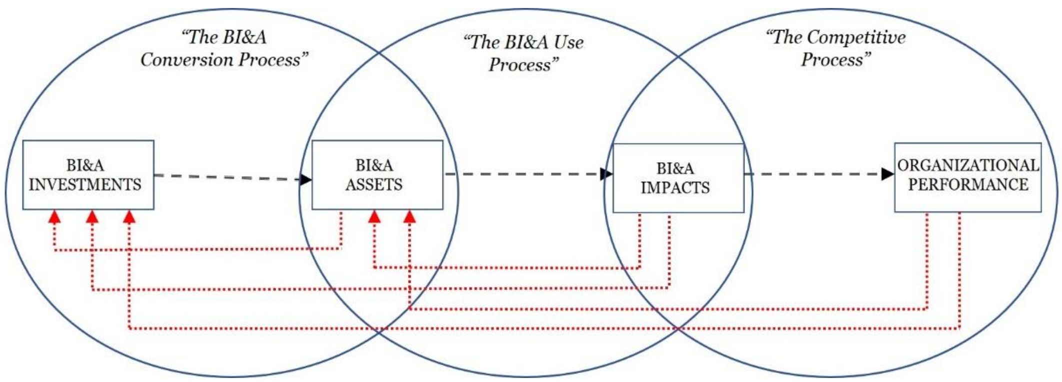

Figure 2. Revised Framework of how BI&A Creates Value (adapted from Trieu, 2017)

The informants also stressed the importance of creating and maintaining a complete vision of the BI&A effort. We contend that this is important in guiding and motivating the iterative development of the system. In addition, we propose that the BI&A project needs to plan for future flexibility, so that the entire solution will continue to deliver value to the business over time. We propose that using this strategy can lessen the factors derailing the success of BI&A initiatives. Therefore, future studies should focus on this issue.

Second, we found that there are several new options for implementing BI&A without a data warehouse. The informants considered this to be an appropriate solution for small businesses. Data warehouses can be large, complex, and costly for SMEs. BI&A without a data warehouse can help bypass the traditional complex data warehouse process. According to the interviewees, SMEs have adopted BI&A tools such as PowerBI, Tableau, and QlikView to run their business without building data warehouses. With a wide range of affordable BI&A tools now available, small enterprises that have no real need and no budget for BI&A projects can start with these tools. In addition, the data from our interviews illustrated how SMEs are realizing benefits from adopting these tools to improve their reporting and applying simple analytics on top of their BI&A environments. Hence, it is feasible for SMEs to skip the data warehouse part of a BI&A project. We found no studies on the benefits or problems of BI&A without data warehouses in the literature. Therefore, studies that assess the validity of this approach, as well as what such BI&A tools can offer to SMEs, can contribute to making BI&A more mainstream in SMEs.

Third, the automated data warehouse approach is another means of avoiding the traditional data warehouse project. We found that automated data warehouses can be an appropriate option for SMEs. Algorithms for automating data warehouses are already presented in the literature (Phipps and Davis 2002); however, we posit that there is a need for empirical studies on how automated data warehousing would be a viable alternative to traditional data warehousing.

In addition, we also found that data governance is a neglected issue in BI&A investments. This is consistent with the findings in Kamioka et al. (2016). However, we found no studies on the importance of data governance in BI&A initiatives. We also found that data governance is important for the success of a BI&A project. Therefore, we infer that data governance is also critical for BI&A benefits realization. We propose that data governance should be part of everyone's organizational responsibility to support data governance priorities, standards, and requirements. In addition, basic guidelines for structuring data governance in SMEs needs further investigation.

The results of the interviews show that SMEs are adopting BI&A for various purposes, including automation, having full control over their data, and enhancing their decision-making processes. Various sectors, such as the banking, insurance, finance, production, sales, architecture, private equity, and hospitality industries in Norway have adopted BI&A to run their business more effectively. The literature has demonstrated how BI&A has permeated various industries; however, it has not clearly identified the type of enterprises (Olszak and Ziemba 2006). Moreover, SMEs in Norway are still at a low level of BI&A maturity. We found that they only use the simple analytics functionality of BI&A. One reason could be that business managers may not be aware of the advanced BI&A capabilities. Therefore, we argue that we need further studies assessing SMEs' readiness and capabilities for BI&A. In addition, studies should also address how BI&A is applied in SMEs in various industries.

We found that the experts' main perceived BI&A impacts for SMEs are business insight, customer insight, cost reduction, and competitive advantage. The literature points to a wider set of potential BI&A impacts (Ranjan 2009; Watson and Wixom 2007) and has proposed methods for measuring and assessing these impacts (Gibson et al. 2004; Hočevar and Jaklič 2010). However, to attain the full benefits of BI&A, the systems need to be used effectively (Burton-Jones and Grange 2012). The literature has demonstrated few studies on the effective use of BI&A (Trieu 2017). Hence, empirical studies on the effective use of BI&A in SMEs would be a valuable avenue for future research.

Conclusion

This has been an exploratory investigation of how BI&A creates value for SMEs. We interviewed 24 experts from both the vendor and the client sides. We identified many issues, three of which were perceived as particularly important. First, an iterative and gradual investment strategy is preferable for SMEs. Second, there are several new options for implementing BI&A without a data warehouse, and the informants considered this to be an appropriate solution for small businesses. Third, the experts pointed out that an automated data warehouse approach would often be the most suitable option for SMEs. In addition, we contribute to the BI&A literature by proposing a modified BI&A value creation framework for SMEs.

Our research was exploratory and performed in one country. Therefore, it has limited generalizability, providing possibilities for future research. This research can serve as input for subsequent studies on BI&A use in SMEs. It would be interesting to see if our findings are generalizable to other countries. Even if we cannot generalize the findings, the study and its findings should serve to enlighten SMEs about the pertinent issues related to BI&A adoption.

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DRIVERS OF BUSINESS INTELLIGENCE-BASED VALUE CREATION: THE EXPERTS' VIEW

Research full-length paper

Track N°1 Big Data and Business Analytics Ecosystems

Llave, Marilex Rea, University of Agder, Kristiansand, Norway, marilex.r.llave@uia.no

Olsen, Dag H., University of Agder, Kristiansand, Norway, dag.h.olsen@uia.no

Abstract

The field of business intelligence (BI) has become increasingly important in both research and practice in recent years. However, research on the business value of BI is still scarce. This study investigates the factors influencing how BI creates business value. Through an exploratory study, we conducted interviews with 16 BI experts from different industries. The experts highlighted four significant drivers of BI-based business value creation: (1) building a business case, (2) formulating a BI strategy, (3) data governance, and (4) organizational adaptability. In addition, this study outlines how BI creates business value. Research gaps and suggestions for future research are also presented.

Keywords: BI value, business case, BI strategy, data governance, organizational adaptability.

1 Introduction

Most top organizations around the world use data for decision-making. They have shifted their focus to data rather than depending on business acumen alone. In today's competitive, knowledge-based economy, organizations are struggling to make sense of the fast-increasing volume, velocity, and variety of data (IşıK et al., 2013). This has resulted in growing pressure to provide better and quicker responses to customers (IşıK et al., 2013). Moreover, it is widely recognized that information plays a crucial role in the success or failure of organizations (Citroen, 2011).

Business intelligence (BI) is used to collect, analyze, and disseminate data so that organizations can make informed decisions (Hedgebeth, 2007). Coined by the Gartner Group in 1990s, the term *BI* came to embrace a variety of information technology (IT)–based tools and approaches that help organizations make better use of the increasingly vast amounts of data accumulated from both internal and external sources (IşıK et al., 2013). Therefore, many organizations have turned to BI applications as a means of improving organizational decision-making (IşıK et al., 2013). BI is currently the largest area of IT investment in organizations and has been rated as the top technology priority of CIOs worldwide for many years (Arnott et al., 2017). It has emerged as one of the critical applications in companies not only to support decision-making, but also to provide useful insight and drive organizational performance (Cruz-Jesus et al., 2018). BI has thrived in almost every industry including retail, financial services, manufacturing, utilities, and telecommunication services. Hence, both practitioners and researchers have created enormous demand for employing BI (Ali et al., 2018).

The information systems (IS) literature has shed light on the positive impact of BI-derived information on decision-making (Popovič et al., 2012). In addition, BI has gained popularity by having the ability to shape the way an enterprise conducts its business. Although BI research is a growing trend in IS research, research on the business value of BI is still scarce (Elbashir et al., 2013). Moreover, whether and how organizations achieve business value on the basis of their BI investments remains unclear.

Therefore, it is crucial to understand how BI creates business value and to identify what the most relevant drivers for BI-based business value creation are.

The main purpose of this paper is to improve the understanding of the drivers of BI-based business value. We conducted exploratory research on 16 BI experts from different industries to investigate the drivers affecting BI-based business value creation. More specifically, the paper will address the following research question: What are the factors influencing the BI business value creation process? The paper is organized as follows. Section 2 presents the research background of this study. We then describe the method used for data collection in Section 3. After reporting on the findings in Section 4, the discussion and implications are presented in Section 5. Finally, limitations and conclusions are discussed in Section 6.

2 Background

As a concept, BI is not novel. Since BI was first mentioned by the pioneer of information science, H.P. Luhn, in 1958 (Luhn, 1958), it has been defined in a myriad of ways, and the concept is still evolving. Forrester typically defined BI as a set of methodologies, processes, architectures, and technologies that transform raw data into meaningful information, which is then used to enable more effective strategic, tactical, and operational insights and decision-making (Evelson and Nicolson, 2008). BI is also often used as the umbrella term for large-scale decision support systems in organizations (Arnott et al., 2017). The Data Warehousing Institute defines BI as the processes, technologies, and tools needed to turn data into information, information into knowledge, and knowledge into plans that drive profitable business action (Loshin, 2012).

The concept of BI has attracted substantial attention from both practitioners and academics. Due to today's competitive environment, organizations require the assistance of BI to make informed decisions, which results in increased demand for BI. Therefore, BI has been a popular topic among researchers and scholars in the field of IS and strategic management (Ahmad et al., 2016). Hence, an extensive literature on BI has emerged.

Deploying BI is a complex, time-consuming, and expensive undertaking, because these software applications are high-risk/high-return projects (Ahmad et al., 2016). Improper implementation of BI may lead to failure and in turn render organizations data rich and information poor. Therefore, BI is highlighted as one of the most risky IT investments, requiring collaboration among IT and business executives to generate business value (Wagner and Weitzel, 2012). Many practitioners have thought that BI evolved from being a reporting tool and has gone far from being only a part of IT departments (Vizgaitytė and Rimvydas, 2012). Moreover, BI has penetrated all decision levels, from strategic and tactical down to operational level support. Strategic decision support typically involves the analysis of a large amount of data that must be "sliced and diced" in various ways. Tactical decision support often requires repeatedly accessing only a limited amount of data for short-term decisions (Watson et al., 2006). By contrast, operational decision support often introduces the need to make faster decisions based on both an organization's current state and details of its recent history (Wynn et al., 2007).

In general, the most important research questions in the field of IS involve measuring the business value of IS (Melville et al., 2004). Business value is also predicted to remain one of the major research topics for IS researchers (Schryen, 2013). Although the BI market appears vibrant and the importance of BI systems is more widely accepted, how organizations achieve business value on the basis of BI has yet to be fully investigated (Elbashir et al., 2013). Whether and how organizations obtain business value from BI is still unclear. As one of the fastest developing business application areas, BI has created a trail of confusion regarding its potential as a source of value creation (Vizgaitytė and Rimvydas, 2012). Therefore, both practitioners and researchers have continued to investigate the business value of BI (Trieu, 2017). For these reasons, it is more critical to understand the drivers of BI-based value creation to ensure the success of this promising, yet risky and costly, technological innovation.

Few studies have addressed the business value of BI. A study by Elbashir et al. (2013) discussed the role of shared knowledge and assimilation as a way to enhance the business value of BI. They argued that BI systems' assimilation and the need for shared knowledge among the strategic and operational levels are the drivers of BI-derived business value. A study by Trieu (2017) reviewed the IS literature to shed light on the processes by which organizations obtain business value from BI. Trieu's work presented the three processes on the framework of how BI creates value as shown in Figure 1.

First, the BI conversion process includes the link between BI investment and BI assets. BI investment consists of investments on BI related hardware, software, and technical infrastructure, human resources and management capabilities. BI assets consist of BI technology, human resources, and application portfolios. BI investment results in better performance and is a necessary but insufficient condition for BI assets. Second, the link between BI assets and BI impacts involves the BI use process. BI impacts refer to a state in which enterprises have attained benefits from BI, such as improved operational efficiency of processes, new/improved products or services, and/or strengthened organizational intelligence and dynamic organizational structure. According to the literature, high-quality BI assets are a necessary but insufficient condition for achieving BI impacts. Lastly, the link between BI impacts and organizational performance depends on the competitive process. Organizational performance includes measures of successful goal accomplishment, satisfaction of constituents, and the ability to gain valued inputs from scarce resources. However, BI impacts are important and necessary but are insufficient to result in improved organizational performance. Further, we have utilized Trieu's framework to illustrate BI-derived value creation.

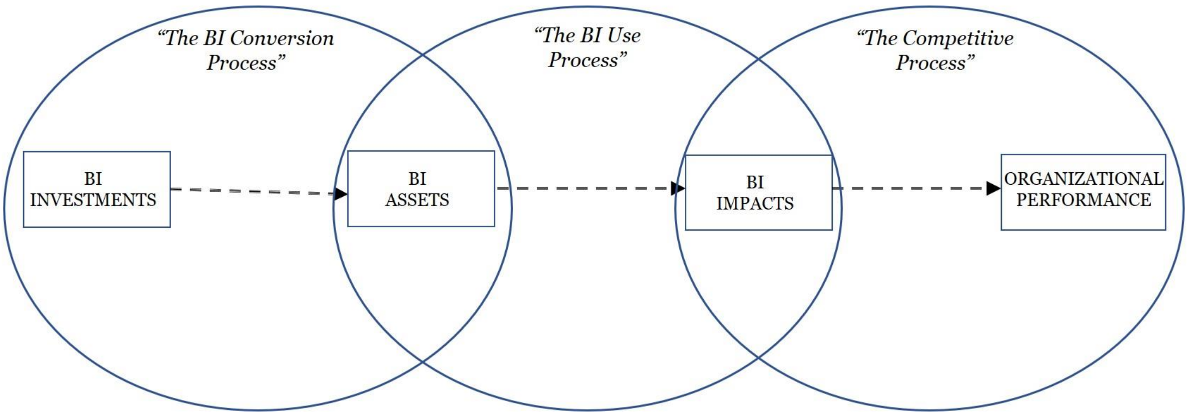

Figure 1. BI value creation (adapted from Trieu (2017)).

3 Method

In this study, we used the expert interview technique developed by Meuser and Nagel [21]. The data were collected from 16 semi-structured interviews with BI experts from different Norwegian industries. The experts were identified using LinkedIn based on their appropriateness as informants for this study. An overview of the informant's roles is presented in Table 1. Each interview took 30 to 45 minutes and was digitally recorded. In the interviews, the informants were probed for information regarding what, according to their experience, BI, BI business value, and BI technologies are.

NVivo was used to transcribe and analyze the interviews. This study used thematic analysis guidelines developed by Braun and Clarke (2006) for data analysis. The guidelines comprised six phases of analysis. In the first stage, researchers familiarize themselves with their data. In this phase, the data were read and reread, while taking down initial ideas. The second phase is generating initial codes. In a systematic fashion, the interesting features of data across the entire data set were coded, and the data relevant to each code were collated. The third phase is searching for themes. The codes were collated into potential themes, and all the data relevant to each potential theme were gathered. In the fourth phase, all the themes were checked in relation to the coded extracts from the first phase and the entire data set from the second phase. The fifth phase is defining and naming themes. The overall analysis was reviewed to generate clear definitions and names for each theme. Finally, a report of the analysis, which is presented in the findings section, was presented. All the data were analyzed by the first author.

Position	**Industry**	**Company Size**
BI Advisor	Consulting and Advisory Services	Small
Senior BI Advisor	BI Software Provider	Small
Senior BI Advisor	IT Consultancy	Large
Data Manager	Banking	Small
BI Project Manager	IT Consultancy	Large
Data Scientist	IT Consultancy	Large
BI Developer	IT Consultancy	Large
BI Developer	IT Consultancy	Small
Senior BI Architect	Banking	Small
Senior BI Architect	IT Consultancy	Large
Head of BI	IT Consultancy	Large
Head of BI	Agricultural	Large
Head of Analytics	IT Consultancy	Medium
Head of Analytics	IT Consultancy	Large
Head of Analytics	Consulting and Advisory Services	Large
Data Governance Leader	Insurance	Large

Table 1. The informant's role, industry domains, and company size.

4 Findings

This section presents the findings of the interviews. First, we discuss how the informants defined the business value of BI and how BI creates business value. We then present the four important drivers of BI-based business value creation.

4.1 Business value of BI

The informants emphasized three business values of BI: automation, business insight, and decision support. The informants emphasized that automation was the easiest way to achieve business value from BI. They explained that with automated reporting, organizations can use business data to produce reports much faster, with less effort, and without further analysis. One of the informants noted that *"if we start by the lowest hanging fruit it would be automation of collecting, integrating, and making data available. Provided that they already produce that stuff manually, one key value would be automating it because that results in cost-reduction."* Therefore, most informants maintained that most organizations are adopting BI for ease of use in exploring data, as well as scalability in automating reports. Another informant stated that *"automating reports is reducing the cost of creating reports. And what you actually reduce are two things: you reduce the manual effort of collecting and putting together data, and you also reduce the effort of providing reports to end users. So, I would separate it into data collection, preparation, and distribution. Distributing reports is a big job, especially if you have a bigger organization."*

Another aspect of automation that most informants mentioned is automated decision-making. Most of them argued that the business value of automated decision-making is easy to quantify. As one of the informants noted: *"The business value of automated decision is mainly due to reduced need for human workforce, which is usually the highest expense and the increased speed of the decision making."* In addition, several informants mentioned that in automated decision-making, the type of decision is crucial. They explained that the type of decision that is typically automated is operational decisions, possibly tactical but probably not strategic decisions. The operational decisions have the kind of volume that justifies automation and they tend to be highly repeatable. Tactical decisions may also be automated if they are complex enough and reasonably high in value, but the informants typically found that they did not want to automate the entire decision so much as to support or guide it. One informant illustrated this point: *"I think most decisions you don't want to automate, a process can be automated if the decision is generally rule-based, then you need to find out all the different conditions and the outcome when we make those decisions? But if it's a decision that a person needs to make based on experience, based on something that it's not possible to write down in a set of rules, then you can't automate that using machine learning."*

Many informants also pointed out that having business insight is a business value derived from investing in BI. By utilizing a BI application as a single data repository, the whole organization can analyze the same version of the numbers and work from a single factual source to gain information and valuable insights. As most informants explained, a simple connection among multiple data sources and the easy creation of reports and dashboards using simple BI tools, such as Power BI and Tableau, will allow organizations to get what they need and get on with their job, with little or no help required from IT. They also mentioned that with business insight, organizations can monitor their performance in the light of history, goals, and peers to keep it focused and on track. One of the informants explained the business value of having insight: "*So you can actually get the insights to all your workers. So, for instance, you know facility services, instead of being a manager telling them what to do all the time, they can have the insight themselves about which part of the building has been in use, how many people have been at the toilet, how many people have been in the canteen, so they can better plan their own day, so they can be more efficient without a manager."* Moreover, several informants pointed out that having a BI system in an organization would offer the same version of the facts or a single version of truth. One of the informants noted that: "*If you have a data warehouse, you get to gather information from several sources and you also clean the data, make the data unified. It saves you quite a lot of energy and you will have one single truth which is quite important because you see that all department people gather for quarterly reports or monthly reports."* He further argued that the advent of data warehousing enables company to retain, clean, load, and integrate vast amounts of data from various sources into a single and standardized repository, allowing them to have the same version of facts as business value.

Finally, most of the informants emphasized that decision support is the most significant business value of BI. They mentioned that BI is built to support decision makers at all levels of an organization with facts that help them make better and more informed decisions. This is illustrated by the following quote from one informant: *"We used BI to make the decision-making process easier and less based on gut feelings. So, it's kind of the end game, so it doesn't matter if you're talking about the data warehouses or data analytics, or machine learning or the internet of things, the whole point of doing anything BI related is to make the decision-making process more secure, easier, and based on facts and not on gut feelings."*

Most informants argued that the classical business value of BI is making decisions based on facts instead of gut feelings. Another informant explained the business value of decision support: "*If the BI solution provides the information needed to be aware of what needs to be improved, the main part of the value gained from this improvement should be credited to the BI solution and not only the action performed as a result."* However, one informant argued that business insight and decision support are two sides of the same coin: *"When you have insight, you can use this insight to give value to the organizations. The insight will first of all be used for decision support. But it can be decision support on all levels, it can be for operational decisions, tactical decisions, and strategic decisions."* Further, most informants emphasized that BI should be the foundation of all decisions, regardless of discipline or business area.

4.2 Drivers of BI-based business value creation

The informants emphasized four important drivers of BI-based business value creation: building a business case, having a BI strategy, data governance, and organizational adaptability. Table 2 presents definitions of each driver according to the informants and the literature.

Drivers	Definition according to experts	Definition according to literature
Business Case	An evaluation of the cost of implementation and maintenance. It is used to financially evaluate and identify tangible and measurable benefits.	The underlying arguments or rationales supporting or documenting why the business should accept something (Carroll and Shabana, 2010).
BI Strategy	A roadmap to help organizations measure their performance and identify competitive advantages.	A strategy that deals with people, process, technology and methodology for BI excellence (Boyer et al., 2010).
Data Governance	A business matter that deals with data quality, data architecture, and data ownership issues.	A collection of capabilities or practices for the creation, capture, valuation, storage, usage, control, access, archiving, and deletion of information over its life cycle (Tallon et al., 2013).
Organizational Adaptability	The ability of an enterprise to cope with new problems, new technologies or methodologies to gain competitive advantage.	The capacity to make crucial change in order to respond proactively to dynamic environments (Dolata, 2013).

Table 2. Definitions of the drivers of BI value creation.

According to most informants, building a business case is normally used to get funding for BI projects or to gain the executive's approval. They also mentioned that they had in fact started a BI project without developing a business case. Typically, a business case is built to identify the problems or opportunities that are being addressed, according to most informants. Tangible and measurable benefits of BI investment are financially evaluated, whereas intangible benefits and positive effects of BI for the entire organization are defined in a qualitative manner. A business case also includes an evaluation of the cost of BI investment and its maintenance. One of the informants stated that *"business case is just kind of how to describe what you're doing and why you're going to do it. You kind of need to build a business case to get the funding for your project. So, the business case is just the executive talking to the IT department. And they agree that we do this for the next two weeks."* Another informant also described the importance of business cases in value creation: *"You need to have a business case, if a data scientist finds something in a real world, then you need to show and tell the business value of it to the managers, or the managers' manager. They need to see where's the money? And where's the value? Because they are always looking for what's in it for them? Is it to improve customer retention? Is it to improve the sales?"*

One informant, a BI vendor, explained the importance of building a business case for small enterprises. He explained that business cases help clients set up key performance indicators (KPIs) together with the decision makers and align them with the strategy. KPIs vary from company to company; for instance, some of their clients wanted to focus on increasing their sales to have better control of sales, profit, or customer lifetime value. Another informant, a client of this BI vendor, argued that business cases have helped them understand the value derived from their BI investment. And they are currently expanding the BI investment across the whole organization. Because they have realized the value derived from BI by looking at the business case they built at the beginning of the project, it was easy for them to decide to invest more. Several of the informants from the large enterprises explained that business cases are not as important for them. They argued that when an organization is planning to execute a BI project with its own resources, the business case is less important. In addition, they mentioned that depending on the culture of an organization, some would just build a business case and present only high-level and intangible benefits. This is because the top management believes that it is obvious that a BI investment will pay off. This is illustrated by the following quote from one informant: *"We never looked at business case again because in the first place we only build the business case to convince the C-level to invest in the project."*

The next factor that influences how BI creates business value is having a BI strategy. Several informants highlighted the importance of BI strategy. They explained that having a BI strategy serves as a roadmap to help organizations measure its performance and identify competitive advantages. Ultimately, they argued that BI strategy gives BI investment and BI assets a goal and direction. One informant stated that *"strategy in general, any kind of strategy is about finding where you are, what's the current situation, and then you define where you want to go, your goals and targets, and then you define how you get there, what are the actions to get there. [...] It's good to have a BI strategy because it creates awareness of the value of BI solution, BI capabilities and stakeholders' commitment."* He argued that a BI strategy begins at the top; it requires executive participation. If the leader of an organization is not fully onboard, then a BI strategy will be a watered-down approach. In addition, a BI strategy gives an organization's BI a goal and direction. A BI project without a goal will certainly provide insight to an organization; however, it will not lead the organization to any destination. According to most informants, in order to get the most insight out of the data, the organization must have a clear BI strategy in place.

Another factor that influences BI value creation is data governance. Most informants explained that data governance is not an IT matter, but a business matter. They argued that the people who build the data warehouse have a technical mindset and that they therefore treat the data issues as technical issues. One of the informants noted that *"the IT should own the solution where the data is modeled but the business side should own the business rules and the meaning of the data. So, each business unit should have data governance that has control over the business rules and the data modelled in the data warehouse."* He argued that when the business side views data management as an IT issue, they always fail to realize that they are in fact part of the data quality problem and do not feel the responsibility to help in solving the data quality issues. According to most informants, data governance is still a new profession, and that is why most organizations still fail to see the need for it. Several informants emphasized the importance of data governance in any BI project. As one informant observed, "*data governance is important. And if you can compare it to data quality, data quality is just one of the issues in a governance project. What governance really means is that you have a rule set for handling your data. And in regards of data quality, it's in regards of data architecture, it's in regards of data ownership. The governance will kind of fall and do all of those things that will help you utilize your data better and maintain your data strategy better."*

Most informants explained that many BI projects fail due to data quality issues—and data quality is one of the main issues exposed by BI. In addition, they mentioned that many organizations discover their data quality issues only when they begin using their BI assets. When the dashboards do not look as nice or useful as they expected, the data quality issues become apparent. One informants said that: *"Data quality, I guess that's the biggest problem with the BI implementation. That we're ready even for production and the data quality is still poor, and it can be very difficult to make the management support or invest in data governance initiatives because it's a very new role. [...] You need that to make sure the quality of your data. Today, data is getting more valuable. That's why you need to have a data governance function in place in order to get this value from BI solutions.*

Finally, most informants considered organizational adaptability an important factor in BI-based business value creation. They defined organizational adaptability as the capacity of an enterprise to cope with new problems, technologies, or methodologies in an effort to gain competitive advantage. Organizational adaptability is the willingness of an organization to look for new opportunities, ideas, and technologies that may improve organizational performance. However, most informants mentioned that this is difficult to achieve and very challenging. According to most informants, many organizations continue to resist change. As a result, the informants found it very challenging to change the company culture. However, several informants presented some ideas on how to improve organizational adaptability. First, most informants underscored the importance of having executive sponsorship or BI ambassadors for a BI project. One of the informants said, *"The challenge is that you need to have the organization behind you, the top management need to be the BI ambassadors for you, and if you find some new insight that you have to go in your market then they need to know how to apply the actions based on your insight."* Second, several informants mentioned that making the organization understand the need to change to leverage BI assets can improve organizational adaptability. The third idea was to provide a BI asset that can improve their business process. For example, one informant stated that *"the most important [thing] is to give the user something that is much better than what they used to have. That's how simple it really is. If the user of the BI gets something that is better, more intuitive, takes less time than what they used to do, and trustworthy then you'll win."* Fourth, informants observed that setting up goals supports the change. Most informants argued that goals should be as specific as possible to help set everyone's sights on the same prize. Lastly, informants emphasized the importance of simply sticking with the process of change. As most of the informants explained, every organization needs to understand that the change needed for a successful BI takes time.

5 Discussion and Implications

In this section, we discuss the most significant findings of the study. Our findings revealed four drivers of BI-based business value creation: building a business case, formulating a BI strategy, data governance, and organizational adaptability.

First, most of the informants emphasized the importance of building a business case. Like any other investment, BI investment should be commercially viable in the eyes of management. A business case is used to demonstrate that BI is worth the investment. Although most organizations need to justify and get approval for IT investment, our interviews revealed that some organizations can still embark on a BI project without building a business case. We also found that in order to ensure that BI can support the strategic objectives of an organization, a business case should be part of the business strategy and have a clearly defined purpose. According to Hočevar and Jaklič (2010), estimating the value of BI requires answers to at least two questions: What are the costs of implementing BI? What are the benefits conferred by implementing BI? Our interviews revealed that these issues are addressed when building a business case. Therefore, we contend that building a business case when embarking on a BI project influences the business value creation derived from BI. However, we found little studies on business case (Dyllick and Hockerts, 2002, Carroll and Shabana, 2010). We propose that further studies should address this issue.

The informants also stressed the importance of formulating a BI strategy. Creating a BI strategy involves identifying where you are currently, where you want to be in the future, and how you plan on getting there. It is important to identify the business reasons for investing in BI, the strategic goals, and application goals of the planned solution (Hočevar and Jaklič, 2010), because a thorough formulation of business objectives and IT must be established for an organization to derive value from BI (Williams and Williams, 2010). Few studies have addressed the importance of formulating a BI strategy (Ramamurthy et al., 2008). Therefore, future studies should focus on this issue.

The informants believed that data governance is a driver of successful business value creation. BI can be very expensive if the information it provides is not accurate or does not match information needs (Hočevar and Jaklič, 2010). Successful BI should use correct, valid, integrated, and in-time data as well as the methods that will transform the data into decision information (Zeng et al., 2006). As Larcker and Lessig (1980) indicated, that information will be used if it is perceived as being sufficiently significant and usable for the decision-making process. According to previous studies, there is a positive relationship between the quality of information and information use (Petter et al., 2008, Citroen, 2011). Data governance can help improve the data quality. Therefore, we contend that data governance can enhance this positive relationship, which can result in a BI-based business value creation. However, few studies have addressed the importance of data governance. A recent study by Janssen et al. (2017) argued that data governance can influence the quality of big data. Moreover, Tallon et al. (2013) discussed the structures and practices used to govern information artifacts. Tallon et al. argued that once an organization adopts data governance, it can boost the organization's performance, because data governance can unlock the value of the data in the organization. We conclude that data governance is a critical driver of BI-based business value creation. Therefore, how data governance influences BI needs further investigation.

The interviews also showed the importance of organizational adaptability in BI-derived value creation. According to Mott (1972), an effective organization displays two characteristics simultaneously: efficiency and adaptability. An efficient organization follows well-structured, stable routines to deliver intelligent products and service. Mott argued that in a changing world, organizations also need adaptability. Most informants mentioned that adaptability is the willingness of an organization to look for new opportunities or ideas that may improve organizational performance. They also explained that adaptability also allows the organization to cope with changes like new problems or technologies. In addition, organizational change is vital if an organization wants to leverage the full BI (Hribar Rajterič, 2010). As mentioned above, the relationship between information quality and information use are two dimensions of successful business value creation. However, Popovič et al. (2012) stated that the attitude towards information use must also be taken into account. We argued that this attitude can be highly influenced by organizational adaptability. We conjecture that improving organizational adaptability will result in better BI-derived business value. However, few papers have discussed organizational adaptability (Motta et al., 2014, Dolata, 2013). Therefore, further studies on how to improve organizational adaptability and how it affects the BI-value creation should be conducted. Furthermore, how BI investment and organizational performance may also be affected by organizational adaptability needs further investigation.

Figure 2 illustrates the four drivers of the BI value creation. First. we argue that business cases influence both the BI conversion process and the BI use process. Building a business case is the first step towards proving the worth of a BI investment. In the business case, the total cost of ownership, expected BI impacts such as return of investment, and cost of risk are discussed to gain executive sponsorship. In addition, both tangible and intangible BI impacts are evaluated. Therefore, business case is used for securing the BI project funding. Further, having a business case will help guide the transition from the old processes to the new BI enhanced processes to achieve the BI impacts.

Second, we believe that the formulation of a BI strategy will affect the entire process of value creation. BI strategy is about knowing the organization's current and future positions and identifying the actions needed to reach the latter. BI strategy supports the planning of software, hardware, human resources, and management capabilities (BI investments) and choosing the right tools, technology, and human resources (BI assets), thus supporting the BI conversion process. BI strategy further supports how BI assets will help to achieve the identified benefits of BI, such as new products/services or better decision-making (BI impacts), thus supporting the BI use process. BI strategy also supports the competitive process. For instance, when an organization have achieved a BI impact to analyze their customers better, this will result in a better ability to target customers. Hence, this contribute to competitive advantage, which through the competitive process may lead to better organizational performance.

Third, we argue that data governance is also an important driver of the BI value creation. Enabling organizations to identify who is responsible for the data is crucial. As stated by most informants, setting policies, creating explicit agreements about how data will be used and determining the impact when data is changed are important in any data management/BI project. In short, data governance is the who, what, how, when, where, and why of data management. It maintains the reliability, validity, integrity and accountability of data that results in a better information quality. In decision-making, quality information is the evident for quality decision (Ali et al., 2018). When BI becomes the vital resource for quality information, then organization will consider BI as the reliable aid for decision-making. In addition, the selection and adoption of BI assets depends on its data environment (Trieu, 2017). Thus, data governance supports the BI conversion process.

Finally, the organizational adaptability influences the BI use process. As mentioned above, the organizational adaptability will influence the attitude of an organization towards the use of BI. Organizations with a higher organizational adaptability will be more able to do the necessary organization adaptation in order to utilize the BI assets. Thus, organizational adaptability is important for the BI use process.

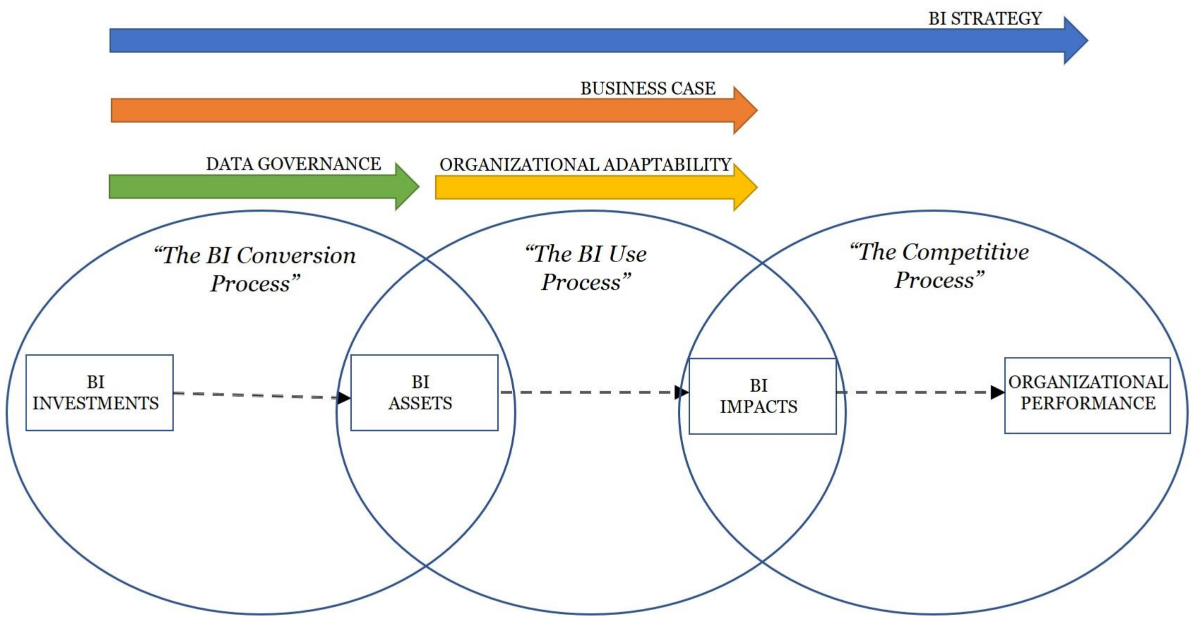

Figure 2. Framework of how BI creates business value (adapted from Trieu (2017)).

Further, we found that the experts believed that automation (automated reporting and automated decision-making), business insight, and decision support are the main business values of BI. They argued that from these, the organization will achieve revenue optimizations, cost reductions, risk reductions, and the ability to enter new markets and develop intelligent products and services. BI impacts have been a main focus of BI studies over the last 15 years; however, the BI literature has been silent on how these BI impacts complement other internal and external factors to create business value (Trieu, 2017). Therefore, we propose that further studies should address this issue.

6 Conclusion

In this exploratory study, we investigated the factors influencing how BI creates business value. We interviewed 16 BI experts from different industries and identified four drivers of BI-based business value creation: building a business case, formulating a BI strategy, data governance, and organizational adaptability. Building a business case is critical, because it influences the BI conversion process and the BI use process. Formulating a BI strategy affects the entire process of BI-derived value creation. Data governance plays a significant role in the BI conversion process. Finally, organizational adaptability influences the BI use process, which is vital to establishing a successful competitive process. The findings of this study can serve as a guide to practitioners embarking on a BI project and can help researchers engage in more BI business value research. However, this study suffers from an important limitation: it was performed in only one country. It would be interesting to determine whether the findings of this study are generalizable to other countries, both developed and developing.

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Data lakes in business intelligence: reporting from the trenches

Marilex Rea Llave*

Department of Information Systems, University of Agder, 4604 Kristiansand, Norway

Abstract

The data lake approach has emerged as a promising way to handle large volumes of structured and unstructured data. This big data technology enables enterprises to profoundly improve their Business Intelligence. However, there is a lack of empirical studies on the use of the data lake approach in enterprises. This paper provides the results of an exploratory study designed to improve the understanding of the use of the data lake approach in enterprises. I interviewed 12 experts who had implemented this approach in various enterprises and identified three important purposes of implementing data lakes: (1) as staging areas or sources for data warehouses, (2) as a platform for experimentation for data scientists and analysts, and (3) as a direct source for self-service business intelligence. The study also identifies several perceived benefits and challenges of the data lake approach. The results may be beneficial for both academics and practitioners. Further, suggestions for future research is presented.

Keywords: Business intelligence; big data; data lake; BI architecture.

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: marilex.r.llave@uia.no

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1. Introduction

Business Intelligence (BI) is a contemporary approach that combines methodologies, processes, architectures, and technologies to transform raw data into meaningful information for decision making [1]. BI can play a vital role in improving organizational performance by identifying new opportunities, highlighting potential threats, revealing new business insights, and enhancing decision making processes [2, 3]. Therefore, BI is a top priority for organizations in most industries [4]. Traditionally, BI focuses primarily on structured and internal enterprise data, overlooking potentially valuable information embedded in unstructured and external data. This could result in an incomplete view of reality and biased enterprise decision making [5].

The accelerated growth and pervasive development of internet, web, and cloud technologies have given new meaning to the phrase “information overload” [6]. These technological advances have led to the generation of unprecedented volumes and accumulations of data. Large and complex data are often described by the concept of “Big data” [7]. As big data become increasingly available, the challenge of analyzing large and growing data sets is growing more urgent. Therefore, BI today faces new challenges, but also exciting opportunities [5].

Big data was one of the big buzzwords of the 2000s [8]. The first organizations to embrace big data were online and start-up companies. According to Davenport and Dyché [8], companies like Google, eBay, and Facebook were built around big data from the beginning. Big data changed the way enterprises manipulated data, providing not only new opportunities to handle data, but also new ways to use and add value to vast amounts of data coming from the Internet of Things (IoT), social media, web logs, and sensors [9]. Big data also supports the supply of data as a resource that organizations can utilize [10].

Big data has also led to the emergence of modern technologies like data lakes, which enable enterprises to store and handle large volumes of structured and unstructured data in their native format. However, despite the prevalence of this technology, our literature search yielded only a handful of studies discussing data lakes. One study discussed data lakes in a cursory manner [11], while another [12] discussed some of the challenges of data lakes in a detailed fashion. However, we found no empirical studies on the use of data lakes in enterprises.

The main objectives of the study are to understand the role of data lake in a BI architecture and how data lake is used in practice by enterprises. The following research questions have guided this research:

What are the purposes of implementing data lake into a BI architecture?

How do data lakes affect the BI architecture of an enterprise?

What are the benefits and challenges of implementing data lake in a BI architecture?

Since the topic has not been empirically examined in prior research, this study conducted exploratory research of BI experts from various industries. In the next section of this paper, I discuss the theoretical background for this study. Then, I illustrate the exploratory study approach by describing the data collection and the data analysis procedure. Subsequently, I present the results of this exploratory study. The article ends with a discussion of the research findings, directions for future research, and a conclusion, as well as the study’s limitations.

2. Theoretical background

The term Big data refers to the huge growth of data that organizations are currently experiencing [2]. Big data can also refer to technological developments in data storage and data processing that make it possible to handle exponential increases in data volume in any type of format [13, 14]. Another recognized definition of big data is based on the 3-V model [2], which comprises three dimensions of challenges in data growth: volume, velocity, and variety. Volume refers to the growing amount of data. Velocity describes the speed of new data creation and the speed of data accessibility for further analysis. Finally, variety describes the range of different data sources and types. More recently, scholars have proposed a fourth V: value, which stresses the importance of doing something valuable with data [14].

BI is strongly interrelated with big data because BI provides the methodological and technological capabilities for data analysis [13]. BI is an overarching term for decision support systems that use data integration and analysis to improve decision making [15]. Therefore, it is widely used to describe a variety of different information analysis applications that support informed decision making based on wider knowledge [16]. A typical BI architecture comprises a data source layer, an Extract-Transform-Load (ETL) layer, a data warehouse layer, an end user layer, and a metadata layer [17]. Of these layers, the data warehouse layer is one of the most important. Data warehousing involves moving data from a set of source systems into a target repository [16]. The extracted data are then sent to temporary storage called the data staging area [18]. The transformation of the data describes the process by which data are converted using a set of business rules into consistent formats for reporting and analysis. These transformed data are then loaded into the data warehouse. Therefore, the data warehouse can also be defined as the central storage that collects and stores data from internal and external data sources to support tactical and strategic decision making [19].

The term big data was coined to describe the changing technology landscape that resulted in vast amounts of data, a continuous flow of data, multiple data sources, and multiple data formats. Data are the underlying resource for BI [14]. Arguably, it is the increasing availability of data that serves as the impetus for change for BI projects and methodologies [11]. Modern technologies like data lakes have made it possible to acquire data without a full understanding of the data's structure [11]. A data lake is a repository for large quantities and varieties of data, both structured and unstructured [20]. The term was first coined by James Dixon, the chief technology officer (CTO) of Pentaho, to convey the concept of a centralized repository containing virtually inexhaustible amounts of raw data for analysis or undetermined future use [12]. Data lakes also offer storage and processing power to support the analysis of large and unstructured data sets.

Enterprises across various industries are beginning to place their data into data lakes without performing any data transformations [20]. The extant literature contains few studies on data lake technologies. Larson and Chang [11] conducted a study in which they defined the data lake concept. They argued that the data lake technology has emerged as new type of data repositories that enables storage and processing power to support the analysis of large unstructured data sets. A study by Terrizzano et al. [12] presented and described the challenges of data lake technologies. They proposed a simple method for handling the following issues: data selection, description, maintenance, and governance. Several studies have presented the integration of data lakes with enterprise systems such as Enterprise Content Management (ECM) and Enterprise Resource Planning (ERP). In ECM, data lakes are used to capture, create, index, search, access, organize, and maintain all organizational content regardless of the data format [21]. Therefore, ECM packages can support al kinds of data from well-structured data to unstructured data. ERP used data lake so that the data can be collected once during the initial transaction, stored centrally, and updated in real time [22]. However, no studies have yet empirically examined the use of data lakes in enterprises. In addition, the BI literature has been silent on how data lakes affect BI architectures.

3. Research method

In this exploratory study, the expert interview technique by Meuser and Nagel [23] was used. Data were collected from 12 semi-structured interviews with BI experts from different industries in Norway. The experts were identified using LinkedIn based on their appropriateness as informants for this study. In addition, a snowballing technique was used in which each informant was asked to recommend other possible informants. An overview of the informants' roles is presented in Table 1. Each interview took approximately 30 to 60 minutes and was digitally recorded. In the interviews, the informants were probed for information regarding BI implementation, BI architectures, and data lake technologies, based on their experience.

All the interviews were transcribed and analyzed using NVivo. To conduct the data analysis, Braun and Clarke's thematic analysis guidelines [24] were used, which define six phases of analysis. In the first stage, the author familiarizes herself with the data. In this phase, the data were read and re-read while noting down initial ideas. The second phase involves generating initial codes. The interesting features of the data were coded in a systematic fashion across the entire data set and the data relevant to each code were collated. The third phase involves searching for themes. The codes were collated into potential themes and all the data relevant to each potential theme were gathered. The fourth phase is reviewing themes. Here, the author checked whether the themes worked in relation to the coded extracts from the first phase and the entire data set from the second phase. The fifth phase involves defining and naming themes. In this phase, the overall analysis was reviewed to generate clear definitions and names for each theme. Finally, a report of the analysis was produced, which is presented in the results section.

Table 1. The informants' roles and industry domains.

Role	Industry	BI Experience (year)
Head of BI	IT Consultancy	11
Head of Analytics	Insurance	10
Head of Analytics	Public Sector	20
Data Manager	BI Software Provider	10
Head of Data Warehouse	IT Consultancy	7
BI Advisor	BI Software Provider	17
Data Governance Leader	Insurance	10
BI Architect	IT Consultancy	20
Data Scientist	IT Consultancy	6
Data Scientist	IT Consultancy	10
BI Consultant	IT Consultancy	8
Business Analytics Consultant	Insurance	10

4. Results

This section presents the results of the interviews. First, I present how the informants define the data lake approach, followed by the perceived benefits of data lakes. I then examine the purposes of data lakes in enterprises and explore their challenges.

The informants defined data lakes from two perspectives: a technology perspective and a business perspective. From the technology perspective, one informant stated that a "Data lake, for me, is the collection of technologies with data that you need to store in some specific format. So, a data lake is not one data lake; it's many technologies that serve the data's need." Most informants also explained that a data lake is a central repository of any type of data and a central repository of truth. However, a few informants also defined a data lake from a business perspective. For instance, one of the informants mentioned that a "data lake, for me, is a capability of the business where you can get raw, unchanged data that are from different source systems." This informant also stated that "a data lake is the place where I can get all the data in our enterprise."

4.1. Perceived benefits of data lakes

The informants emphasized four perceived benefits of data lakes: the reduction of up-front effort through data storage, better data acquisition, quick access to raw data, and data preservation.

First, a majority of the informants emphasized that data lake reduces up-front effort because they ingest data in any format without requiring an initial schema. They explained that this early ingestion and late processing of data is one of the innovations of data lakes. One of the informants stated that "this is similar to ELT, where the T is performed last and sometimes defined on the fly as data is read." Similarly, one informant explained that "When you got the data lake concept, you could choose to store the data because you did not have to define the data [with respect to] how you [were going to] store it, […] because that is quite time-consuming. So, with the data lake, you can say, 'I just want to store the data, because storing the data is such a low cost that it's actually cheaper to store them than not to have them when I need them.'" The informants expressed that data lakes gave them the opportunity to defer schema development and data clean-up until the enterprise had identified a clear business need.

Another benefit of data lakes that several of the informants identified was that they make acquiring new data easy. One of the informants noted that, "In the data lake, you just say, 'We just dump all the data in there.' We take all the data from the sources we put into the data lake […] because this is much faster than doing all this work to restructure the data." The informants also noted that a data lake can store all types of data, resulting in less effort during data acquisition. Furthermore, one informant stated that, "[Very] often, you are not allowed to go directly from the source systems to fetch data because there are policies, like 'Do not disturb operational systems.' So that's why they need a copy of the data. And the data lake formalizes these things, so you have one place, one pool, for all the data." Another informant said:

> From the time the data scientists or the analysts need the data and the time you put the data into the data lake, that time is very short. And the reason why it's short is because we don't apply business rules to the data: We just dump the data there, and there is no format. So, basically, when we put data in the data lake, it's just basic governance around it. It's just like making sure that we have the right access control and also that the data is tagged in the right place.

Therefore, this informant argued, acquiring new data into a data lake requires little effort.

The interviews noted that another benefit of data lake is that they provide quick access to raw data. Most informants argued that having quick access to raw data is beneficial to any enterprise. For example, one informant noted that, "With the data lake, first of all, the data will already be there [...] So that means, when the business users ask a question, the data scientists or analysts can go in there, fetch the data, and do their transformation of the data, so it will correspond with the business question. So that is much faster." In addition, one of the informants compared data lakes to data warehouses, stating that, "Many of the data warehouses, they actually have frisked all the errors; they have taken all the data which is not based on one reason or another [...] A data lake gives you access to all this information which is never used anywhere. It can be records that are not even visible in the source systems based on errors." Therefore, the informants argued, data lakes make data quickly available, especially for data science, analysis, and research and development.

Finally, many informants considered preserving data in their native form to be one of the benefits of data lakes. Most of the informants emphasized the importance of having access to raw or untouched data. For example, one informant said, "When the data has been transformed, aggregated, truncated, and updated, most organizations typically struggle to connect the data together." Similarly, another informant stated that, "When you have a data warehouse […], you never read in all the tables. You leave the unimportant ones, which someone has deemed unimportant. But then, there's another person who wants to do analysis on exactly that data that someone else has deemed unimportant, and that person cannot do it because he cannot have access to it in the data warehouse." Similarly, one of the informants stressed the importance of raw data by stating that, "In my mind, all the data have some kind of structure, and then you say you cannot use this data—it's not for that exact purpose—and then you put it into models. But to me, the models, they are just that: They are not the truth. The truth is up on the raw data." Finally, the informants pointed out that, when data are preserved in their original form, they can be used repeatedly as new business needs emerge.

4.2. Purposes of data lakes

The interviews revealed three purposes of data lakes: as staging areas or sources for data warehouses, as a platform for experimentation for data scientists or analysts, and as direct source for self-service BI, as illustrated in Fig. 1.

First, most informants stressed the importance of utilizing data lakes as staging areas or sources for data warehouses. As mentioned earlier, a staging area is a temporary location between a data source and a data warehouse. This is illustrated by the following quote from one informant:

> The staging area is a storage [area], typically a relational database, to temporarily keep a copy of the source data as a step on the way to the data warehouse. In the extension, the staging area is also used to store temporary result sets from calculations and transformations as a part of the ETL processes. The main purpose of the [staging area] is to avoid heavy processing and potential overload of the source system that might be critical for businesses when transforming the data on the way to the data warehouse. […] A data lake is a storage [area that keeps] a permanent copy of different types of source data, both structured and unstructured. The main purpose of the data lake is to keep data both for current defined needs and [for] future undefined needs. The data in the data lake is stored as it is extracted, on the same data structure as in the source system or as received, without any transformations.

One of the informants pointed out a downside of staging areas. He stated that:

> When the Internet of Things and sensors come into play, you need someplace to store all these various data that comes from new technology. [...] To be able to store that data, relational databases, like SQL, would

> not be fit for this purpose. Then, the data lake came up, and the sole purpose of the data lake is to store the unstructured data or the odd data that comes from middle things, like sensor devices and web logs.

Second, several informants talked about using data lakes for storing histories or archiving. They explained that data lakes can also be used for offloading archived data from data warehouses. Therefore, all informants argued that a data lake is a useful component in any data warehouse architecture and that it can be seen as an extension of the concept of BI.

Many informants also pointed out the use of data lakes for data science and advanced analytics. According to most of the informants, data scientists and business analysts are the "power users" of data lakes. The informants also noted that data lakes are useful for exploration and advanced analytics. For example, one informant stated that, "My thought is, you can do analytics directly in the data lake, and then, when you've found some good data, or the data scientists come up with an extremely good algorithm or model, then you should move the result of that algorithm into the data warehouse and report that way." Another informant noted that:

> When you fetch some data from the data warehouse, we've already applied a lot of rules to the data, like transformation rules. And when we apply transformation rules, we also sort of put make up on the data. […] So, that also means that some information might be lost, like, for example, on an attribute, there is a missing value in the source, but on the way in, we cleansed it so that it becomes zero instead of missing. So, to a data scientist or an analyst, that could be very specific and important information because missing might mean that the customer was never asked, for example, while zero might mean that the customer was asked, but said no. So, this kind of thing might be lost in translation. So, to avoid things [getting] lost in translation, it's good to have one source that you can go to and then build up the business rules from scratch.

The informants also noted that data scientists and analysts can use data lakes for research and development. As one informant described:

> There are also other things that a data scientist can do in the data lake. You can experiment, like research and development, so that you can be more specific, and you can be more familiar with the data before you ask or order the data into the data warehouse. […] So, the data scientist might be more familiar with the data before you specify specific transformation rules, for example.

In addition, the informants noted that data scientists often execute R scripts from their local workstations to conduct exploratory data science and advanced analytics on data lakes. Therefore, one of the informants note that, "I would look at the data lake as a sandbox for the data scientists and analysts, really. They use it for data exploration and development of models".

Finally, several informants mentioned that data lakes can be used as direct sources for self-service BI. One of the informants noted that, "If you need a new report, then we can build that directly on the data lake. [...] So we use self-service BI directly on the data lake, plus in concert with the data warehouse. We apply a semantic layer in between the data lake and self-service BI tools." Some of the informants also explained that data lakes can be used to provide data for BI reporting and analytics tools.

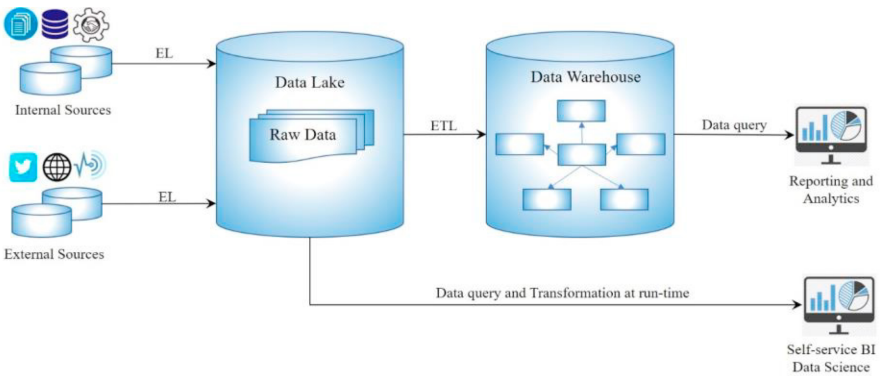

Fig. 1. different purposes of data lakes

4.3. Challenges of data lakes

The interviews also revealed several challenges related to data lakes, including challenges related to data stewardship, data governance, skills needed for analytical purposes, data quality, and data retrieval.

First, most of the informants pointed out data stewardship is one of the most important challenges of data lakes. One of the informants stated that, "The thing that lacks from the [data lake] is data stewardships […] It is important to know what this data is. Even unstructured data can be dumped into it. But if you have clickstreams coming into it, then it should be well-defined that this is a website level."

The informants also considered data governance to be one of the challenges of data lakes. One of the informants noted that, "You can still set up permissions and such; however, a lot of companies are saying, 'Okay, we will move all our data into this data lake,' and quickly, what happens is, nobody really knows what's in there." In addition, one informant pointed out that, "If you want governance, then you need to move your data into an Inmon or Kimball data warehouse." This informant argued that enterprises that need to secure and obfuscate confidential data may struggle to implement data governance in a data lake.

Another challenge concerns the skills needed to make analytical use of the data in data lakes. One of the informants noted that:

> The issue is, the original format of the data will be in the form that is complex to understand. So that means it has a higher requirement for expertise, for excellence, when it comes to how to prep the data […] That means the analyst, or the data scientist needs to be very good on how to code and manipulate data.

Most of the informants also identified data quality as an important challenge. One of the informants stated that, "So you have some challenges there [in the context of data quality], as well. I mean, it's not just providing data to data scientists. […] So, if the sensor is wrong, there is something wrong with the sensor, but then you expect that the sensor is providing you correct data, then everything will be wrong." In addition, another informant noted that "The data in the data lake is just raw […] The data might look very unclean, and there might be a lot of rubbish there."

Finally, data retrieval poses another challenge related to data lakes. One of the informants explained:

> The difference between a data lake and a data warehouse [is that], in a data warehouse, you transform the data before you store it in the data warehouse. You do all the work in advance. […] For the data lake, you have the data in the original format, so to create insight, you have to do it afterwards. So, there, you just have to […] take the data you need, and to build a program to cleanse it to standardized or consolidate it for your specific purpose. So that means every time you need the data you have to do a lot of work, because nothing is done for you in advance.

Most of the informants argued that data lake technologies involve less effort during data acquisition, but more effort during data retrieval.

5. Discussion and Implications for Future Work

In this section, I discuss the most significant findings of this study. The informants highlighted three uses of data lakes: as staging areas or sources for data warehouses, as a platform for experimentation for data scientists and analysts, and as direct sources for self-service BI tools.

First, most of the informants believed that it is better to utilize data lakes as staging areas for data warehouses than to use relational databases. Traditional BI leverages the concept of a staging area to stage data from multiple data sources, thereby reducing dependency on the data source and reducing conflict on decision making processes when the same data at different data sources are not updated simultaneously [25]. A data lake is very similar to a traditional relational database staging area; however, there is a key difference: a data lake can store both structured and unstructured data (e.g. data from sensor devices, web logs, clickstreams, or social media), while a relational database cannot. The use of relational databases leads to problems such as deficits in the modeling of data, constraints of horizontal scalability, and big amounts of data [26]. Two trends that emphasized the limitations of relational database are exponential growth of the volume of data generated by users, systems, and sensors and the increasing interdependency and complexity of data accelerated by the internet, social networks, and web. Data lakes can ingest any data type from any data source, and there is no need to define data structures or relationships [27]. In this regard, I find that data lakes can reduce data warehouse storage needs. They also offer practical functionality related to the data they store. This implies that data lakes can offer more than simply storage for large volumes of multi-structured data. Future studies on how data lakes can replace and improve upon normal staging areas in terms of cost, capabilities, and implementation, therefore, are needed.

In addition, I also found that data lakes and data warehouses often coexist. The benefits of data warehouses are numerous: They save time for users, improve the quantity and quality of information, inform decision making, improve business processes, and support the accomplishment of strategic business objectives [28]. Data warehouses provides governance, reliability, standardization, and security; however, implementing traditional data warehouses requires extensive and lengthy processes of data ingestion. It can take months to even see the results of the input data. In this context, data lakes can offer agility, flexibility, rapid delivery, and data exploration benefits to complement data warehouses. I contend that utilizing the data lake technologies can help improve enterprises' data warehouse environment and enable agile BI. Therefore, future empirical studies should examine the range of data lake technologies currently available in the market and explore the use of data lakes to extend data warehouse environments and provide agile BI.

Second, I found that data lakes also serve as a platform for experimentation for data scientists and analysts. "Data Scientist are the people who understand how to fish out answers to important business questions from today's tsunami of unstructured information" [29] (p. 73). Data scientists and analysts work closely together in the decision making phase, according to Davenport and Patil [29]. Most of the informants considered data scientists and analysts to be the power users of data lake technologies. According to the literature, data lakes intended to serve as "sand boxes" for data scientists [30]. Both data scientists and analysts benefit the most from data lakes because they have the necessary skills to understand the data's content, structure, and format. Data obtained in their raw form are often not suitable for direct use by analytics; they are often challenging to obtain, interpret, describe, and maintain. Thus, data scientists and analysts conduct step-by-step processes to prepare the raw data for analytical purposes[12]. Moreover, our results suggest that using data lake as a sandbox for experimentation can be vital. Therefore, I recommend that future studies should address these issues in more detail.

Finally, data lakes can be used as direct sources for self-service BI. However, this is a topic which is not discussed in the literature. The interviews offered no information explicitly describing the implementation of this purpose. Therefore, there is a need for future studies addressing this use of data lakes.

I also found that the most important perceived benefits of the data lake approach were: the reduction of up-front data storage effort, better data acquisition, quick access to raw data, and data preservation. These benefits enable enterprises to move data across various sources to quickly derive business outcomes. I believe that data lake technologies can extend traditional BI systems to meet wider business needs. I therefore propose that the BI literature should address the benefits of data lakes in BI implementation and the benefits of data lake deployment in business in more detail.

Like any other technology, data lakes pose certain challenges. Through expert interviews, I uncovered several challenges related to data lakes. These challenges involve data stewardship, data governance, skills needed for analytical purposes, data quality, and data retrieval. Data lakes are the next evolution of technologies for the storage and analysis of both structured and unstructured data. However, they represent a complex solution; therefore, the challenges of data lake implementation require more attention in the literature.

6. Conclusion

This paper investigated the capabilities of data lakes in enterprises. An exploratory study was conducted to understand data lake technologies and provided insights into the perceived benefits and purposes of data lakes. This study found that data lakes integrate seamlessly with a variety of data sources and data warehouses. Though data warehouses continue to meet users' information needs and provide important value to enterprises, data lakes offer rich sources of data for data scientists, analysts, and self-service data consumers, while also serving the needs of BI and big data. This paper makes three contributions to the BI literature: data lakes are used as a staging area for data warehouse; data lakes serve as a platform for experimentation for data scientists and analysts; and data lakes can be used as a direct source for self-service BI. The bottom line is that data lakes do not replace data warehouses; rather, they augment or complement the data warehouse architecture. Hence, data lakes should be considered extensions of the BI architecture. The study also identified several challenges related to data lakes. A deeper awareness of these challenges could benefit organizations seeking to embark on data lake projects.

Like any study, this study has some limitations. Although this exploratory study drew on experts with knowledge and experience in data lakes, the experts came only from large enterprises. Therefore, all the results are based on the experiences of experts from large enterprises. Furthermore, this research represents only one exploratory study; therefore, it has limited generalizability. Despite these limitations, however, the findings of this study can provide important inputs for future empirical research on data lakes.

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Creating strategic business value from BI&A: Navigating the dire straits between investment and performance

Abstract

Business intelligence and analytics (BI&A) solutions have become one of the most crucial information technology investment in enterprises to achieve strategic advantage. In contrast to the wide adoption among large enterprises, adoption among businesses in general is still limited. Small and medium sized enterprises, which make up more than 99% of enterprises in market economies, have different information systems (IS) adoption patterns from that of large enterprises. The research on BI&A adoption remains insufficient, and our knowledge of BI&A adoption issues reflects the special case of large enterprises. This study seeks to fill this gap by offering important insights into BI&A adoption through a grounded Delphi study. Data were collected by combining a ranking-type Delphi with qualitative interviews. We identified core categories of drivers and inhibitors, and we theorized how they influence the BI&A value creation process. Organizational readiness was found to be the most important inhibitor. We developed recommendations on how to improve organizational readiness. This study adds to the growing body of research on business analytics and decision environments in organizations. The empirical findings extend our knowledge of organizational readiness' role in IS adoption. Implications for future research are also discussed.

Keywords:

Business intelligence and analytics; strategic business value; organizational readiness; decision environment; small-and medium-sized enterprises; grounded Delphi

1. Introduction

Business intelligence and analytics (BI&A) has become an increasingly important subject in information systems (IS) research (Chen, Chiang, & Storey, 2012; Holsapple, Lee-Post, & Pakath, 2014), and studies on BI&A and related topics is a growing field of research (Arnott & Pervan, 2014; Chiang, Grover, Liang, & Zhang, 2018). The BI&A approach comprises concepts and methods that offer analytical capabilities to improve decision making in business processes. Raw data are transformed into meaningful information that assists decision makers at different organizational levels (Clark, Jones, & Armstrong, 2007; Wixom & Watson, 2010). BI&A systems and related technologies are considered the most significant information technology (IT) investments in organizations (Kappelman, Johnson, Torres, Maurer, & McLean, 2019), not only for supporting decision makers but also for increasing business value and improving organizational performance (Trieu, 2017; Vallurupalli & Bose, 2018). Accordingly, BI&A has been among the top five most influential technologies on a global basis for the last 10 years (Luftman et al., 2015). The specificities of these systems are pivotal in assisting managers as they deal with crucial information resources through sophisticated extraction and drilling down, and they enable core data visibility, effective reporting, prediction analysis, and market forecasts to sustain and strengthen competitive positions in the global business environment (Popovič, Hackney, Coelho, & Jaklič, 2014). It has been observed that high-performing organizations make decisions based on a more thorough and intensive precision analysis than do low-performing organizations (Sharma, Mithas, & Kankanhalli, 2014). Moreover, evidence suggests that a strong analytical decision-making culture is one of the most important factors for the successful utilization of these systems (Popovič, Hackney, Coelho, & Jaklič, 2012).

Succeeding with BI&A investments, i.e. realizing business value, usually requires substantial changes to managerial and organizational processes (Davenport, 2006; Elbashir, Collier, & Davern, 2008; Watson & Wixom, 2007). A BI&A adoption will therefore be a multi-faceted phenomenon, and research on BI&A adoption need to address a complex socio-technical environment (Fink, Yogev, & Even, 2017). However, research has focused mostly on the technological aspects of BI&A, for example, different BI&A components and their implementation (e.g., data warehousing, data mining, digital dashboards, and data visualization) (Ain, Vaia, DeLone, & Waheed, 2019; Ranjan, 2009). In contrast, we know very little about the socio-technical factors for BI&A adoption (Larson & Chang, 2016; Liang & Liu, 2018), and knowledge about the adoption phenomenon is limited and lacks empirical evidence. A recent literature review also revealed that BI&A research suffers from a lack of empirical grounding and insufficient theoretical development, and that the diffusion of knowledge from the literature on IT value to that of BI&A value had been sporadic and inconsistent (Fink et al., 2017). It is therefore important to identify and understand how socio-technical factors influence companies' ability to successfully adopt and achieve value from BI&A.

The BI&A approach and its systems have been highly attractive for large companies for several decades. In contrast, there have been a very slow adoption of BI&A in the small- and medium-sized enterprises (SME) sector (Popovič, Puklavec, & Oliveira, 2018). Therefore, research on critical issues for BI&A adoption has mainly focused on large enterprises (Olszak & Ziemba, 2012). Thus, our knowledge of BI&A adoption issues reflects the large enterprise context, and it may not be valid for enterprises in general. SMEs comprise approximately 99% of all companies in developed countries and provide 70% of the total jobs in the market (OECD, 2017). We therefore argue that SMEs are representative for the general population of enterprises. The slow adoption of BI&A among SMEs is therefore a significant problem for all developed economies. It is therefore crucial to gain more knowledge about how SMEs consider and prioritize new digital investments (Li, Liu, Belitski, Ghobadian, & O'Regan, 2016), especially how they adopt BI&A.

Typically, SMEs have scarce resources, small budgets, and limited technical expertise, and they are slow adopters of new technologies (Zach, Munkvold, & Olsen, 2014). This creates potential barriers preventing them from adopting innovative technologies that can improve organizational performance (Levy & Powell, 2000). Small organizations also have different technology adoption patterns compared with large companies. Financial obstacles and a lack of technical knowledge are two of the most important hindrances to IT progress in SMEs (Iacovou, Benbasat, & Dexter, 1995). On the other side, SMEs have more informal structures than larger companies, and their resources, capabilities and business processes are idiosyncratic in nature. SMEs can therefore be more responsive to dynamic environments and more susceptible to digital innovations than larger organizations (Chan, Teoh, Yeow, & Pan, 2019).

Despite the significance of BI&A, very little is currently known about BI&A adoption in SMEs. With the exception of a few recent studies (Popovič et al., 2018; Puklavec, Oliveira, & Popovič, 2018), no previous research has given sufficient attention to the determinants of BI&A adoption or non-adoption in SMEs. It is therefore important to explore how socio-technical factors impact SMEs' ability to effectively adopt and realize value from BI&A.

This study aims to fill the research gap by providing a deeper understanding of BI&A adoption (and non-adoption) and value creation in SMEs. We want to achieve this in several ways. First, we want to achieve a better understanding of the reasons for adopting BI&A. We therefore address the drivers for BI&A adoption. Then, we also want to achieve a better understanding of why SMEs are reluctant to adopt BI&A. We therefore address the inhibitors for BI&A adoption. Finally, we address why these factors are important. We have therefore formulated the following research questions (RQs):

RQ1: What are the drivers for BI&A adoption in SMEs?

RQ2: What are the inhibitors for BI&A adoption in SMEs?

RQ3: Why are these drivers and inhibitors important for BI&A adoption in SMEs?

In this study, we have used a ranking type Delphi study (Okoli & Pawlowski, 2004; Pare, Cameron, Poba-Nzaou, & Templier, 2013). We have used a panel of BI&A experts to generate ranked lists of drivers and inhibitors. These lists were subsequently used as basis for follow-up interviews with panel participants to explore how these factors influence adoption. This is consistent with the ideas and guidelines from the grounded Delphi approach. This specific research method is appropriate for identifying, mapping, and prioritizing the themes of a specific topic that needs to be explored in depth in order to understand the interrelationships between themes (Päivärinta, Pekkola, & Moe, 2011).

This study contributes to two research streams within the IS literature. First, we contribute to the IS adoption literature by providing a deeper understanding of BI&A adoption in SMEs. We identify drivers and inhibitors crucial for BI&A adoption and theorized how they influence the BI&A value creation processes. We also extend our knowledge of the organizational readiness construct. Second, our study adds to the growing body of research on business analytics and decision environments in organizations by focusing on the SME context. Finally, this research provides a set of practical recommendations for decision makers in SMEs that consider adopting BI&A. Particularly, these advices are important to increase the organizational readiness in SMEs.

The remainder of the paper proceeds as follows. First, we present the concept of BI&A, related research on BI&A adoption, and the background for why this research is needed. Second, the methodological approach is introduced. Third, the results and analyses are presented, followed by the discussion and the implications of the results. Finally, we present the conclusion.

2. Related Research and Background

The topic of business analytics (BA) has received considerable scholarly attention in the last few decades and have been the subject of much systematic investigation in IS research (Chen et al., 2012; Sharma et al., 2014). BI&A has become an important technology to improve business performance and strengthen the momentum for developing enterprise, management, and marketing intelligence (Vallurupalli & Bose, 2018). The use of BI&A has also proved to be important in innovation activities, which in turn enhances organizational value and firm performance (Božič & Dimovski, 2019).

BA has been used to describe the applications that support decision-making processes in organizations (Davenport, 2006), but it is also conceptualized as an important foundational paradigm guiding future research studies and educational programs to understand the potential of BA and its practical and theoretical implications (Holsapple et al., 2014). The concept of BI is defined as a "broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions" (Wixom & Watson, 2010). In this paper, the concepts of BA and BI are combined (BI&A) and signify information-intensive concepts and methods for improving business decision making in complex socio-technical environments (Chen et al., 2012).

BI&A is one specific category of IS, and the scope of BI&A in this paper is not limited to technical components only. Like any information system, BI&A comprise both technical and organizational elements, including the decision makers and their decision environment (IşıK, Jones, & Sidorova, 2013). Despite the classification of BI&A as an information system, it is important to note that BI&A systems and operational information systems have some key differences. BI&A systems have specific requirements for achieving success and obtaining the optimal outcome. Such requirements are for example related to information quality and data integration, which involves the complex combination of multiple data sources (Popovič et al., 2012).

In this paper, we seek to understand adoption issues related to BI&A technologies. The IS adoption literature represents a huge body of research. Different frameworks (e.g., technical, organizational, and environmental (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990) and diffusion of innovation (DOI) theory (Rogers, 2010)) have been utilized to understand the adoption of IS innovations. In one study that seeks to determine the impact of electronic data interchange (EDI) adoption in SMEs (Iacovou et al., 1995), the authors found that EDI adopters belonged to different categories (unprepared adopters, ready adopters, coerced adopters, and unmotivated adopters), and the perceived benefits, organizational readiness, and external pressure to adopt varied across these categories. This study demonstrates the complexity of adoption dimensions and how perceptions about adoption and adoption processes can diverge across business contexts.

Previous studies have failed to present convincing empirical evidence of BI&A adoption in SMEs, and there is a relatively small body of literature concerned with a deeper understanding of the factors influencing adoption processes in SMEs. Most of these studies are conceptual in nature and suffer from sparse empirical evidence. A greater part of this literature focuses on developing BI&A adoption frameworks and maturity models (e.g., Boonsiritomachai, McGrath, & Burgess, 2016). One of the first systematic studies of BI&A adoption determinants with some empirical proof, was reported by Puklavec and colleagues (2014). They conducted a literature review of prior IS adoption studies and developed a conceptual model encompassing the highest-ranked IS adoption determinants. In two follow-up studies (Popovič et al., 2018; Puklavec et al., 2018), they tested an extended conceptual model based on IS adoption determinants (TOE and DOI), through a firm-level survey study focusing on the dynamics of BI systems adoption processes in SMEs. They found that having a project champion was the most important factor. In addition, management support was critical in the evaluation and use stage of the DOI, and the level of organizational readiness was mainly important in the evaluation and adoption stages. The authors propose that further research should target an extension of their research framework, to better understand the impact of BI&A adoption and use on organizational performance.

Puklavec and colleagues' (2018) analysis builds on existing theoretical frameworks. We argue that building on general IS adoption determinants may provide insufficient evidence to fully understand BI&A adoption in SMEs. There is a need to use a more open-ended approach and conduct an exploratory study that examines the specificities of BI&A adoption determinants. Furthermore, BI&A technologies have also progressed and changed over time (Gupta, Deokar, Iyer, Sharda, & Schrader, 2018), to keep up with an increasingly heterogeneous data environment that requires advanced data integration from multiple internal and external data sources (IşıK et al., 2013). It is therefore critical to obtain new insights to ensure the relevance of the determinants influencing BI&A adoption in SMEs.

The SME context is also a crucial dimension in this study. Compared with larger companies, SMEs may have different needs for fast and informed decision making. It is therefore important to understand how they can utilize BI&A to become more data driven, and to take advantage of their information in new intelligent modes. The majority of BI&A systems are adopted by larger enterprises, and, thus, studies have primarily paid attention to this context (Scholz, Schieder, Kurze, Gluchowski, & Böhringer, 2010). We argue that the literature therefore may have missed important issues for the wide adoption of BI&A in the economy. Comparing large enterprises with SMEs, significant contextual variations are found in terms of ownership, management style, decision-making behavior, organizational structure and culture, and business processes and procedures. These factors altogether influence their capabilities to adopt advanced technologies (Zach et al., 2014).

3. Research Method

Many approaches would have been appropriate for our study of BI&A adoption in SMEs. However, we wanted an exploratory method that did not constrain us to a set of a priori BI&A adoption drivers and inhibitors. The Delphi approach allowed us to combine an open grounded approach with a structured and iterative ranking process.

The Delphi method has been applied for decades in various fields and is considered an established and legitimate research method (Dalkey & Helmer, 1963). Linstone and Turoff (1975) define the Delphi approach as a "method of structuring a group communication process so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem" (p. 3). The Delphi technique also allows researchers to obtain reliable first-hand data from selected panelists, providing opportunities to process experts' information through multiple rounds of interaction with the goal of reaching a consensus (Okoli & Pawlowski, 2004).

According to Gordon (1994), the Delphi method was designed to encourage a true debate and develop independent personalities in which anonymity and feedback are crucial. Anonymity and feedback are two irreducible elements of the Delphi method. Rowe and Wright (1999) presented statistical group response as the third aspect of a Delphi study. The classical Delphi, the policy Delphi, the decision Delphi, and the ranking-type Delphi are the four main techniques that are extensively used (Pare et al., 2013)

In this study, we utilize the ranking-type Delphi approach to identify the most important drivers and inhibitors of BI&A adoption in SMEs and we determine the relative importance of these items. The ranking-type Delphi is used to reach group consensus about the relative importance of a set of items by utilizing the following steps: assembling experts, brainstorming, narrowing down, and ranking (Pare et al., 2013). In addition, we utilize principles from the grounded Delphi approach to understand the interrelationships between the identified themes and do further theorizing (Päivärinta et al., 2011).

The Delphi method is adopted in IS research and is utilized on a variety of topics. Examples are Delphi studies focusing on the most urgent problems in the interplay between system development and IT operations in system development projects (Iden, Tessem, & Päivärinta, 2011), the most critical skills for managing IT projects (Keil, Lee, & Deng, 2013), the perceptions of IT project risks among senior executives and project managers (Liu, Zhang, Keil, & Chen, 2010), the most important software project risks across continents (Schmidt, Lyytinen, Keil, & Cule, 2001), and the most important issues for adopting cloud computing in enterprises as perceived by different groups of stakeholders (El-Gazzar, Hustad, & Olsen, 2016).

3.1 Assembling Experts

The composition and selection of the panels are of utmost importance to achieve the successful execution of a Delphi study (Linstone & Turoff, 1975). The expertise and quality of the panel members are critical in improving the credibility and validity of the process (Hsu & Sandford, 2007; Okoli & Pawlowski, 2004). However, this process is considered challenging, thus making a Delphi study rather complicated and very time consuming (Dalkey & Helmer, 1963). The extant literature offers no clear indication of an ideal panel size; however, most researchers suggest a panel size between 15 and 50 participants (Kezar & Maxey, 2016). Furthermore, panel stability is considered vital, so no new experts should join the panel after the beginning of the study.

In this study, compulsory and desired criteria were defined to guarantee high-quality panel members on the basis of suggestions from the extant literature (Keil et al., 2013). The compulsory criteria for panel participation are first-hand experience in Norwegian SMEs, no less than five years' working experience in the field of BI&A, and willingness to participate throughout the entire study. The desired criteria consist of working experience in a consulting company, attendance at a BI conference, and participation in BI forums or being active in other BI events in Norway.

This study recruited a total of 43 experts through a LinkedIn search and experts' recommendations. All 43 experts met the compulsory criteria, whereas several experts met two or more of the desired criteria. Most experts are between 35 and 45 years old and have more than 10 years of experience from leading or participating in BI&A projects having either deployed, adapted, or utilized BI&A applications to support decision-making processes in different organizational levels. The experts have experience from a wide range of industries, and they represent both vendor and user organizations of BI&A. The experts' professional roles comprise among others BI consultant, BI manager, BI architect, BI advisor, director of analytics, chief analytics officer, business architect, business analyst, CEO and professor in BI&A. Most experts have higher education from the undergraduate, graduate, or post-graduate levels. Out of 43 experts, 10 are female. The details of the experts are provided in Table 1.

Table 1. Overview of the panelists

Characteristics	Expert Profile
Gender	
Male	33
Female	10
Years of BI experience	
5–10	18
11–15	10
16–20	6
More than 20	9
Higher education	
Bachelor's degree	23
Master's degree	19
Doctoral degree	1

3.2 Data Collection Approach

The data were collected through a ranking-type Delphi method, which was divided into the following three phases: brainstorming, narrowing down, and two rounds of ranking (Okoli & Pawlowski, 2004). In addition, follow-up interviews were conducted with 12 of the panelists (Figure 1). The different phases are presented in the following.

3.2.1 The Brainstorming Phase

In the first phase, a brainstorming round is conducted to collect as many items as possible for each of the two questions examined: (1) What are the drivers (different factors contributing to adoption) of BI&A adoption in SMEs? and (2) What are the inhibitors (challenges, problems) of BI&A adoption in SMEs? Each expert was asked to provide at least five items with supplementary comments for both drivers and inhibitors and, if possible, to justify their importance. The questionnaire was emailed to experts shortly after they gave their consent to participate. As required, reminders were sent by email to encourage the panelists to respond. In this first round, four experts declined to participate because of their heavy workload, and the response rate for the first questionnaire was 91% with a panel size of 39 experts. A total of 435 items were generated by the panelists, and all items were logged into a spreadsheet, discussed, and coded by the authors of this study. Out of 435 items, there were 227 drivers and 208 inhibitors. During this round, similar issues were merged, and combined, and duplicate meanings were removed.

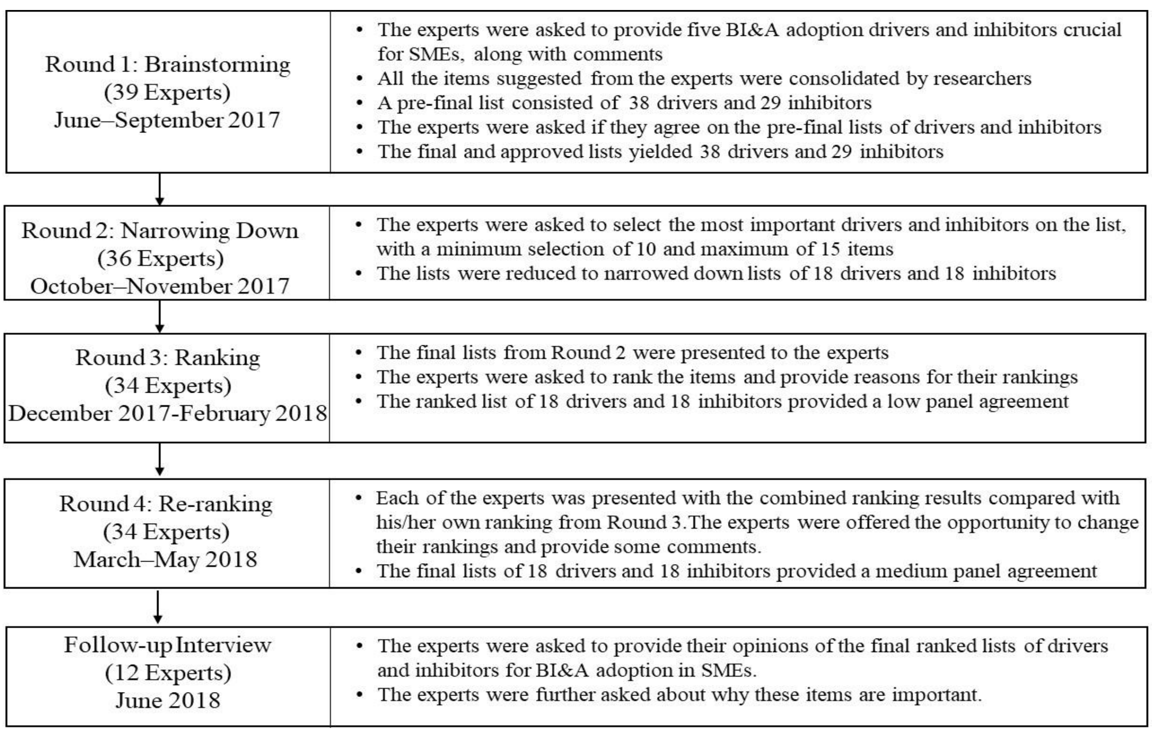

Figure 1. Summary of Delphi phases and follow-up interviews

After reaching 250 items (139 drivers and 111 inhibitors), we utilized the TOE framework (from the innovation adoption literature (Tornatzky et al., 1990) to cluster the items of the drivers and inhibitors into TOE categories. It is important to note that even if these categories are exhaustive, they are not necessarily mutually exclusive. For example, one item may contain both organizational and technological properties.

Through further analysis of the items within this framework, additional combination and merging of the items yielded a total of 67 items. Out of these 67 items, 38 were drivers and 29 were inhibitors. The panel validated the combined list generated from this round to ensure that all items were included and appropriately interpreted by the authors. Tables A1 and A2 in the Appendix show the approved lists of 38 drivers and 29 inhibitors, respectively.

3.2.2 The Narrowing Down Phase

In this round, a randomly ordered list of the 67 items (38 drivers and 29 inhibitors) identified from the brainstorming round was sent to each participant. Experts were asked to select 10–15 each of the most important BI&A adoption drivers and inhibitors. In the survey questionnaire, each item was provided with a brief description to ensure clarity before ranking. This narrowing down phase aimed to reduce the two lists of items into a more manageable number of items of drivers and inhibitors before the upcoming ranking rounds (Schmidt, 1997). The questionnaires for this round had a 93% response rate (36 responses). The items that were selected by more than 50% of the panelists were selected for the ranking phase. Through this process, the combined list of 38 drivers and 29 inhibitors was reduced to 18 drivers and 18 inhibitors (Table 2, Table 3).

3.2.3 The Ranking Phase

This phase focused on ranking the lists of 18 drivers and 18 inhibitors. Experts were asked to rank randomly ordered lists of items to decide on the relative importance of the items. The first round of ranking had a response rate of 94% with a panel size of 34. The consensus of the panel was measured by calculating the mean ranking and Kendall's coefficient of concordance (W) (Kendall & Gibbons, 1990). The Kendall's W values showed low consensus for both drivers (W= 0.17) and inhibitors (W= 0.23).

Consequently, the level of concordance of W=0.7, which is considered a high level of agreement for Delphi studies, was not reached for this round. We decided to perform a re-ranking round with the purpose of increasing the value of the Kendall coefficient. In this round, experts were presented with the average scores and their individual rankings for each item from the first ranking round. They were asked to consider agreeing on the average scores, so they were given the opportunity to change their original rankings. A moderate degree of consensus was reached after the re-ranking round with 34 panelists: Kendall W=0.47 for drivers and W=0.50 for inhibitors. Despite a moderate level of agreement, we decided to stop the number of ranking rounds at this stage; further rounds would probably lower the interest of the participants because they already fulfilled their requirement of participating in two ranking rounds. Adding another round might decrease the validity of the results: it would be difficult to motivate the participants for another round. In addition, we expected the follow-up interviews to provide us with rich insight into the most important drivers and inhibitors. According to Day and Bobeva (2005), follow-up interviews can be performed to increase data validity.

3.2.4 The Follow-up Interviews

Delphi studies can benefit from the conduct of follow-up interviews with panelists by gaining elaborations of the selected list of items (Day & Bobeva, 2005; Keil et al., 2013). The aim is to utilize findings from the interviews and the brainstorming phase to better understand the background for the emergence of the concepts and the reason for their selection.

We therefore conducted semi-structured interviews with 12 of the panelists who agreed to participate after completing the Delphi study. The purpose of these interviews was to gain an in-depth understanding of why BI&A experts considered particular items to be more important than others. More specifically, the experts were asked the following questions: (1) What is your opinion about the final ranked lists of drivers and inhibitors? (2) Why are the top drivers/inhibitors important? (3) Why are some items more important than others? The interviews were conducted face to face or by phone, and each interview lasted for approximately 15–25 minutes. All the interviews were transcribed and analyzed using NVivo. Similar responses were clustered together to form a general response for each question. The process was iterative and involved moving back and forth between the analysis and the data.

3.3 Analysis and Development of Core Concepts: Grounded Delphi

The first objective of this study was to explore, identify, and rank the most important drivers and inhibitors influencing the adoption of BI&A in SMEs. The second was to provide reasons why the determinants of adoption were crucial. We also further examined the connections between the ranked items. We utilized principles from the grounded Delphi method (Päivärinta et al., 2011), and new core concepts emerged iteratively from the findings. In this way, a grounded approach assisted theory development based on the Delphi data. The coding process revealed the interrelationships between items within the main categories (TOE) of drivers and inhibitors. In this analytical process, we also utilized findings from the brainstorming phase and the interviews. Based on this further analysis, five core categories of both drivers and inhibitors emerged by applying principles from axial and selective coding. These concepts are further elaborated in Section 5.

4 Results

Tables 2 and 3 depict the final results and highlight the relative importance of the top-ranked drivers and inhibitors. The tables present the mean ranks and the Kendall's coefficient (*W)* for each ranking round. According to the Delphi panel, it is important to take these items into account for SMEs implementing BI&A solutions. A moderate degree of consensus was achieved in the re-ranking round (W_{drivers}= 0.47, $W_{\text{inhibitors}}$=0.50). We found that the majority of both drivers and inhibitors were classified as organizational. The top drivers comprise 6 technological, 10 organizational, and 2 environmental drivers. The inhibitors encompass 4 technological, 12 organizational, and 2 environmental inhibitors.

Table 2: Ranking results of the top 18 drivers

Ranking	Drivers	Category	Round 3	Round 4
1	The need for a deeper data insight	Technological	5.47	4.10
2	The need to improve organizational efficiency	Organizational	8.59	8.24
3	The need for data integration	Technological	8.21	8.71
4	The desire to improve enterprise performance	Organizational	6.44	9.14
5	The desire to become a data-driven organization	Organizational	9.82	10.10
6	The need for a single version of the truth	Technological	7.94	10.52
7	The desire for data quality and structure	Technological	8.29	13.14
8	The need to achieve effective decision making at all levels of the organization	Organizational	9.21	15.29
9	The need to increase competitive advantage	Organizational	9.41	16.43
10	BI&A is an executive priority	Organizational	12.94	17.10
11	The need to automate data management and reporting	Organizational	9.56	17.48
12	The need for updated and accurate information	Technological	7.53	17.95
13	The desire to achieve customer service excellence and customer insight	Organizational	9.94	18.43
14	The desire to increase profitability	Organizational	8.47	18.86
15	The desire to improve performance management	Organizational	10.79	19.71
16	The need for data visualization	Technological	12.62	22.29
17	Legal compliance	Environmental	12.74	23.71
18	Emergence of the General Data Protection Regulation (GDPR)	Environmental	13.00	25.00
	Kendall's *W*		**0.17**	**0.47**

Table 3. Ranking results of the top 18 inhibitors

Ranking	Inhibitors	Category	Round 3	Round 4
1	Lack of BI&A competence/skills	Organizational	4.94	4.95
2	Limited resources	Organizational	4.85	5.19
3	Cost of BI&A tools and consulting	Environmental	6.56	6.76
4	Poor data quality	Technological	8.94	10.57
5	Lack of BI&A awareness	Organizational	6.76	10.67
6	Lack of a BI&A champion	Organizational	8.74	12.95
7	BI&A project complexity	Technological	10.12	13.00
8	Data security concerns	Technological	13.53	14.19
9	Resistance to change	Organizational	9.03	15.48
10	Lack of an analytical culture	Organizational	9.74	16.00
11	Lack of knowledge about BI&A tools and products	Organizational	8.74	17.00
12	BI&A vendors have business models that are not tailored for small accounts	Environmental	12.91	19.05
13	BI&A is not an executive priority	Organizational	8.91	19.57
14	Lack of technology competence	Organizational	11.03	19.81

15	BI&A requires organizational change	Organizational	11.76	22.43
16	Internal competition for resources	Organizational	11.18	23.00
17	Implementation time requirements	Organizational	11.47	23.05
18	BI&A project scope creep	Technological	11.79	23.52
	Kendall's *W*		**0.23**	**0.50**

After completing the Delphi study, follow-up interviews were conducted. We focused on the top drivers and inhibitors identified in our study. The aim was to determine why the experts found these issues important and to explore and identify the relationships between the various issues identified. Table B1 and Table B2 in the Appendix summarize the reasons for why the drivers and inhibitors were considered important. Quotes from the experts highlight their thoughts on some of the items. Most of these drivers are well known from the BI&A adoption literature, regardless of company size. Several of the inhibitors, however, are specific to SMEs. The interview data supported the findings from the Delphi study and provided central insights to further understand the items. In the following section, we analyze the Delphi results and combine those with the further elaborations of the panelists.

5 Analysis of the main categories of drivers and inhibitors.

The notes from the brainstorming phase and the transcripts from the follow-up interviews helped us organize the drivers and inhibitors into categories. We found that the top adoption drivers relate to the following categories: The need for data management (T), the need for better information and reporting (T&O), the desire for better business operations (O), the desire to improve business value (O), and the need to follow legal requirements (E). The adoption inhibitors relate to challenging organizational data environment (T), BI&A project challenges (T&O), low organizational readiness (O), low organizational change capability (O), and BI&A market challenges (E). Figure 2 and 3 illustrate the categories and maps the drivers and inhibitors into the TOE framework.

5.1 Categories of drivers

We found that the experts initially had different perspectives on BI&A adoption drivers. While some were more concerned with the technical drivers, such as the need for data insight and better integration, others focused primarily on the business drivers, such as the desire to improve organizational efficiency and enterprise performance. This resulted in a very low consensus in terms of Kendall's *W* in the initial ranking. We saw that the experts broadened their perspectives during the re-ranking rounds, as they were influenced by the average scores. In this sense, the panel went through a learning process, and topics that were outside of the individual expert's focus were subsequently taken into consideration. We saw that the experts did not always want to let go of their own ranking; still, the viewpoints of the other panelists stimulated reflections and awareness. We think that through participation in the study, the panel, as whole, was able to expand its perspective on BI&A adoption in SMEs. The results from the brainstorming phase and the follow-up interviews helped us organize the drivers and map the relationships between them. This is illustrated in Figure 2.

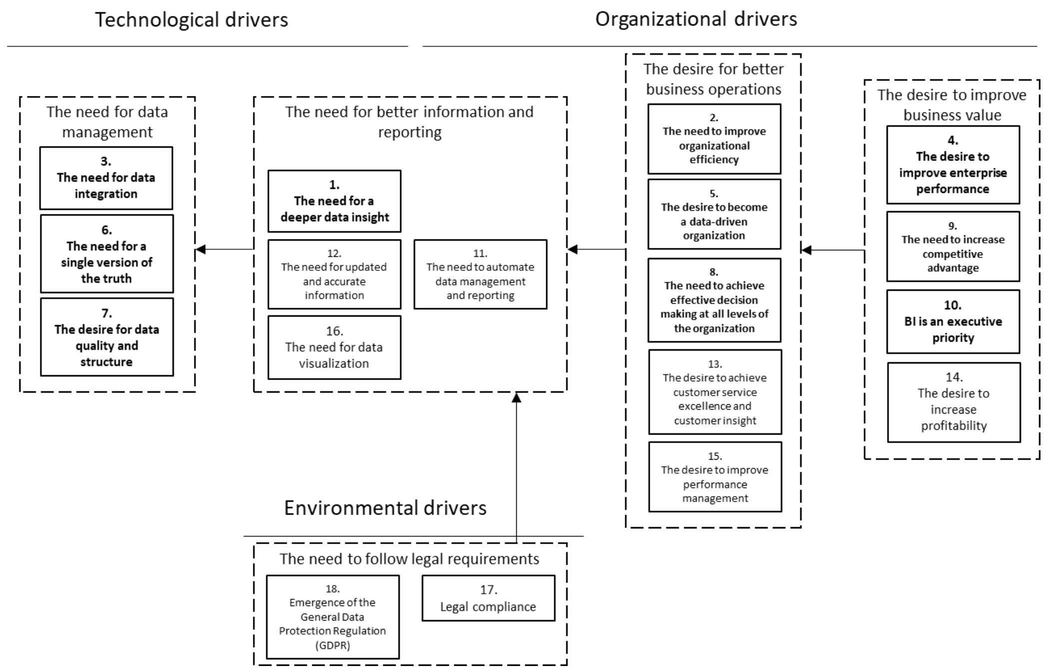

Figure 2. Core categories of BI&A adoption drivers in SMEs and the relationships between the drivers mapped on to the TOE framework (the 10 highest-ranked drivers are in bold).

First, at the highest organizational level, several of the drivers relate to the anticipated business value, such as improved enterprise performance, competitive advantage and profitability (drivers 4, 9, and 14) and, therefore, to the need for having BI&A as an executive priority (driver 10). Therefore, we conjecture that key drivers are associated with the perceived business value from BI&A adoption. We also found that all the other top-ranked drivers are instrumental for achieving such value, but from an operational or technical perspective. We signify this by the arrows in figure 2.

Second, related to these top-level business drivers, the experts perceive a number of more tactical issues, such as more effective decision making and improved organizational efficiency (drivers 2, 5, 8, 13, and 15). These drivers relate to the desire for excellence in business operations, to be achieved with the help of BI&A.

Third, excellence in business operations again requires advanced information and reporting capabilities. Therefore, information and reporting drivers were also prominent (drivers 1, 11, 12, and 16), among which the most important one was the need for a deeper data insight. This is an indication that many of the experts mainly focused on the operational level.

Fourth, advanced information and reporting capabilities require proficient data management. Data management issues were thus seen as important drivers, with three drivers being among the top 10 ones (drivers 3, 6, and 7). This is a reflection of the fact that many organizations run into data complexity problems and lack the ability to utilize corporate data properly, and that this is one of the major drivers of BI adoption efforts.

In sum, by looking at the inter-relationships between the drivers ranked by the expert panel, we see that four core categories emerge in terms of strategic business value drivers, business operations drivers, information and reporting drivers, and data management drivers. We also see that we have a fifth category, legal requirements, such as legal compliance and the emergence of the GDPR (drivers 17 and 18). These drivers were not considered to be among the top drivers for BI&A adoption.

5.2 Framework of Inhibitors

We identified a number of significant inhibitors, that can explain the slow adoption of BI&A in SMEs. The follow-up interviews helped us determine the relationships between the inhibitors and organize them, as illustrated in Figure 3. We combined the inhibitors into five new core categories: low organizational readiness, challenging organizational data environment, BI&A project challenges, BI&A market challenges, and low organizational change capability. The details of the core categories are further elaborated in the following.

First, we found that the general resource poverty of SMEs (inhibitor 2) is an important cause of a number of the other key inhibitors, such as the lack of BI&A competence/skills (inhibitor 1), lack of BI&A awareness (inhibitor 5), lack of knowledge about BI&A tools and products (inhibitor 11), and a general lack of technology competence (inhibitor 14). These inhibitors are related to the organizational readiness construct, which has been discussed in previous literature (Iacovou et al., 1995; Puklavec et al., 2014, 2018). We also conjecture that the lack of an analytical culture (inhibitor 10) can partially be explained by limited resources, which, again, result in low organizational readiness. The lack of an analytical culture is similar to the rational decision-making culture construct in the study of Puklavec et al. (2018).

Limited financial and human resources may be an inhibitor of resource allocation to advance analytical capabilities or hire analysts. We therefore conjecture that SMEs generally have limited resources and that this leads to low organizational readiness for BI&A adoption. Resource poverty can thus be a significant hindrance for the successful utilization of BI&A technologies in SMEs, and we found that low organizational readiness is the most important category. Barriers that can slow down the adoption process relate to several dimensions of the organizational readiness construct, and these dimensions are significant in the SME context. We observe specific BI&A adoption barriers that are related to the SME context du to resource poverty. Resource poverty is therefore an important cause for low organizational readiness.

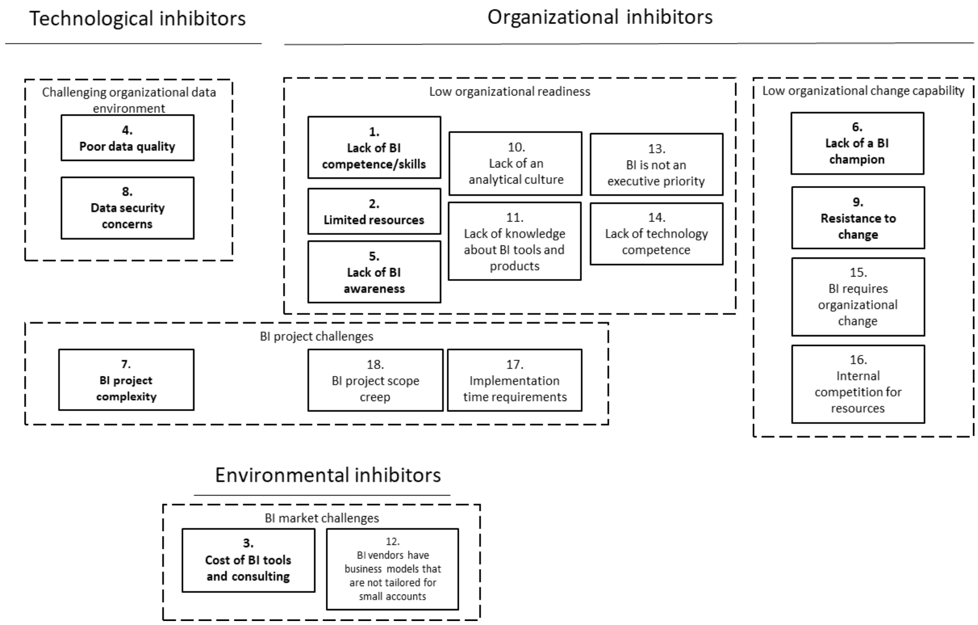

Figure 3. Core categories of BI&A adoption inhibitors in SMEs and the relationships between them mapped on to the TOE framework (the 10 highest-ranked inhibitors are in bold)

Second, organizational change management is also a significant issue in BI&A adoption. BI&A projects are complex and require a significant change to the IT infrastructure and business processes. We observed four inhibitors related to the change management capability. The lack of a BI&A champion (inhibitor 6) implies that it will be difficult to achieve priority for BI&A efforts in the internal competition for resources (inhibitor 16). Puklavec et al. (2018) contend the importance of a project champion to increase organizational readiness. The literature has demonstrated that a change in organizational processes (inhibitor 15) is necessary to realize the most significant benefits and value from BI&A efforts (Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006). The experts in our Delphi panel found that this issue inhibits BI&A adoption. This inhibitor is further aggravated by resistance to change (inhibitor 9). We conjecture that these two issues are closely related, and that they exacerbate each other.

We therefore conjecture that low organizational change capability is an important core category comprising lack of a BI&A champion and resistance in the organization to new digital investments, and to changes in business processes. Organizations with low change capabilities and low IT maturity will struggle with the adoption of new digital investments, such as BI&A.

During the follow-up interviews, many of the experts emphasized an *iterative and gradual process* of investing and building the BI&A asset. Several of the experts used the expression "start small, think big" to denote this strategy. This was seen as important to build commitment in the organization, and thus for the change management. By realizing quick wins, it would be easier to get commitment for further investments. This would contribute to building the legitimacy of further BI&A investments and making the BI&A effort business driven. Several of the experts also emphasized that a BI&A system should evolve over time. Therefore, having an iterative development of the system would make it easier to further develop the system when needed.

Third, we see the challenging organizational data environment is a core category that encompasses the quality of data and their multiple sources, the complexity of data integration, and data security. The high ranking of poor data quality (inhibitor 4) indicates that many SMEs struggle with their legacy data and converting these data into an appropriate format is cumbersome and costly. This issue maps into the "Organizational data environment" construct in Puklavec et al.'s work (2018). On the other hand, inhibitor 8 (data security concerns) is not represented in the constructs of Puklavec et al. (2018). We therefore conjecture that this inhibitor needs to be further investigated.

Fourth, many experts noted that the cost of BI&A tools and consulting is an important environmental inhibitor. This issue was ranked third but is not represented among the constructs in Puklavec et al.'s work (2018). We conjecture that we need to acknowledge that the costs of BI&A tools and consulting is a very important issue for SMEs looking to extend their analytics capabilities. The cost issue is also clearly related to limited resources (inhibitor 2), as costs are more significant when resources are limited. We see this issue in relation to inhibitor 12, the lack of business models tailored to SMEs among BI&A vendors. They both reflect challenges with the BI&A market. We therefore conjecture that BI&A market challenges are also an important core category.

Fifth, the following three issues are related mainly to the BI&A project: BI&A project complexity (inhibitor 7), implementation time requirements (inhibitor 17), and BI&A project scope creep (inhibitor 18). We categorize these items into the BI&A project challenges category.

5.3 Integration and synthesis

We identified several core categories of drivers and inhibitors on the previous sections. Several drivers on the highest organizational level relate to the anticipated business value from the BI&A systems. We therefore conjecture that perceptions about potential business value are important to understand BI&A adoption. In addition, we found that an iterative process was important to realize business value from BI&A investments. Soh and Markus' IS value process model (Soh & Markus, 1995) combines a value perspective with a process focus, and we utilize this model to theorize how the drivers and inhibitors influence the ability to create value from BI&A adoption.

We therefore analyzed each of the core driver categories and found that they related to the outcome and intermediate outcomes in Soh and Markus (1995) model. We illustrate how the drivers influence the value creation processes in figure 4. Comparing the drivers of the first core category of drivers, *the desire to improve business value*, to the Soh and Markus' definitions, we found that this category relates to the organizational performance construct. The three next core driver categories relate to the desired impacts of BI&A assets on the organization, such as better ability to follow legal requirements, better information and reporting and better business operations. They therefore relate to the BI&A impact construct. The last category of drivers, *the need for better data* *management*, is clearly related to the need for BI&A assets, and thus relate to the BI&A asset construct. The relations between the various driver categories and the BI&A value constructs are indicated by dotted arrows in figure 4. The dashed line indicates that strong drivers will lead to a higher likelihood for the BI&A investments.

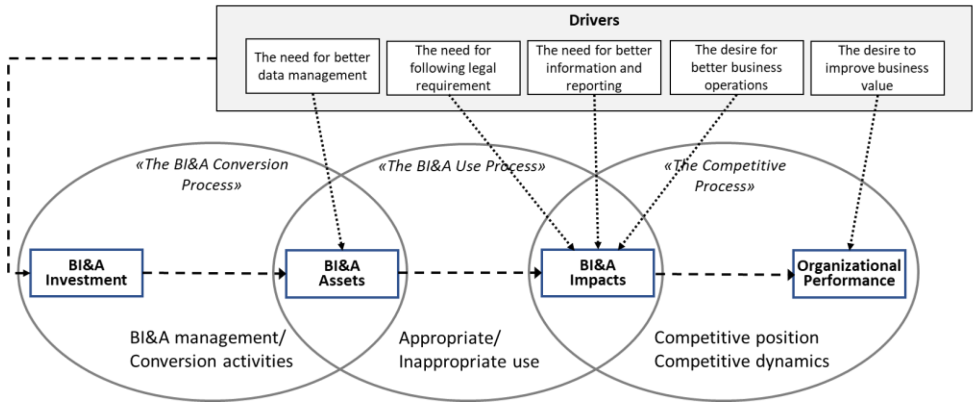

Figure 4. Drivers for BI&A adoption in SMEs mapped on to the IT value process model (Soh & Markus, 1995).

We then analyzed the core inhibitor categories, and we found that the inhibitors would work to curtail the value creation processes. We have illustrated this in figure 4. The impacts of the core inhibitor categories on the value creation processes are indicated by dotted lines in figure 5. *Low organizational change capability* would inhibit the ability to achieve the impacts from the BI&A assets. It would therefore curtail the use process and the ability to achieve appropriate BI&A impacts. Further, we find that *low organizational readiness* mainly relates to the organization's ability to appreciate the utility of BI&A and the ability to implement BI&A assets. Therefore, these inhibitors curtail the BI&A conversion process. The other core categories, *BI project challenges*, *challenging organizational data environment*, and *BI market challenges* all relate to issues that makes it difficult to implement appropriate BI&A assets, and thus works to curtail the BI&A conversion process.

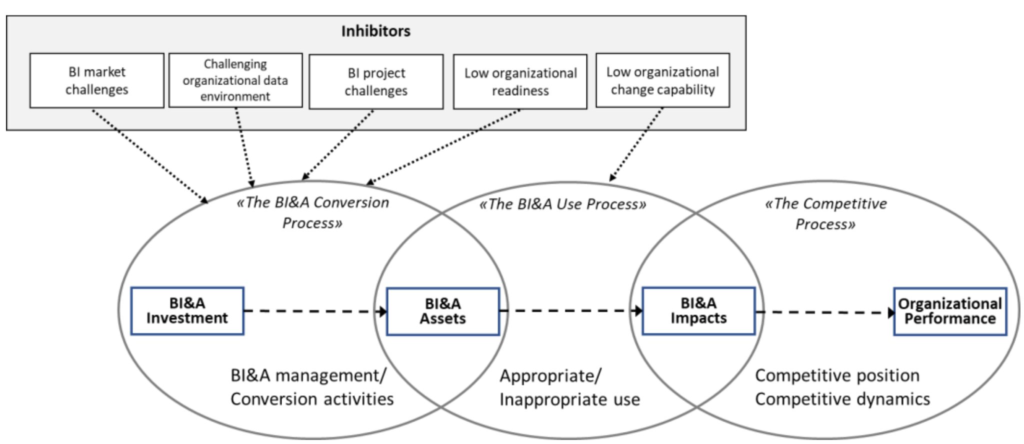

Figure 5. Inhibitors for BI&A adoption in SMEs mapped on to the IT value process model (Soh & Markus, 1995)

6 Discussion and Implications

We have explored how BI&A is adopted in SMEs. By addressing drivers and inhibitors for BI&A adoption among experts, we were able to achieve a better understanding of BI&A adoption in SMEs. We discuss the most important issues below. We also propose recommendations for practice. As argued previously, SMEs comprise approximately 99% of all companies in developed countries (OECD, 2017), and they are therefore representative for the general population of enterprises. As there are few prior studies on BI&A in SMEs, we also compare our findings with literature on BI&A that is not SME specific.

First, we identified several core categories of drivers and inhibitors, and achieved a deeper understanding of how they influence BI&A adoption and value creation. The identified drivers are consistent with findings from research on large enterprises, and we therefore conjecture that they are independent of company size. However, our results indicate that the potential BI&A value -- that are linked to those drivers, will likely be more difficult to realize, due to SME specific inhibitors such as low organizational readiness and low organizational change capability.

The most important core inhibitor category was low organizational readiness, which has also been discussed in previous IS adoption research (Iacovou et al., 1995; Ifinedo, 2011). Nevertheless, only a few studies focus on organizational readiness in terms of BI&A system adoption (Puklavec et al., 2014, 2018). We contribute to this construct by extending it with new dimensions to provide a broader understanding of organizational readiness for BI&A adoption in SMEs. We found that lack of BI&A competence/skills, resource poverty, the lack of BI&A awareness, and the lack of an analytical culture were the most crucial inhibitors of organizational readiness. It is important to address these inhibitors in future BI&A adoption projects.

The findings clearly indicate that resource poverty is a key reason for low organizational readiness and thus a key inhibitor of BI&A adoption in SMEs. The most important items of resource poverty are a general lack of technology competence, including BI&A competence and skills, and limited financial resources. The results are consistent with those of Iacovou et al. (1995) and Puklavec et al. (2018), illustrating how limited resources among SMEs affect adoption processes. We therefore infer that SMEs need to gradually build their competencies related to decision support and an analytical culture and improve their understanding about how they should invest in and utilize BI&A solutions.

As noted by the experts, achieving the most significant BI&A benefits requires significant changes to the IT infrastructure, and this will challenge the status quo in the organization. It will also raise issues on data privacy and security, as well as data ownership (Demirkan et al., 2015). Furthermore, BI&A projects require significant resources, and this kind of IT project need to compete with other pressing issues for funding and top management attention. These issues will all create internal political challenges that may threaten the whole BI&A implementation project. The committed support and priority of top management are therefore important. We thus confirm that top management support is one of the most critical factors to succeed in the adoption of any kind of IS (e.g., Akkermans & Van Helden, 2002; Yeoh & Popovič, 2016), and is generally constituted as the most important risk factor in IT projects (Liu et al., 2010). This finding was also reported by Holsapple et al. (2014), who emphasized the importance of having a management philosophy that understands and supports the use of BI&A.

As all this evidence from this study and previous research shows, technical capabilities are indeed important to succeed with BI&A solutions (IşıK et al., 2013). However, SMEs need to carefully select and prioritize technological capabilities in building their IT competencies, as well as strengthen their organizational readiness. It is important for SMEs to note that BI&A approaches are not *one-size-fits-all* solutions (IşıK et al., 2013). The decision environment and human assets will influence how capabilities develop over time, and the barriers to a successful BI&A adoption are not solely technological in nature (Tian, Chiong, Martin, & Stockdale, 2015).

The results from this study answer calls from recent studies for greater attention to behavioral, organizational, and strategic issues (Kiron & Shockley, 2011; Sharma et al., 2014) and contextual factors (Fink et al., 2017) to understand the BI&A value creation processes in organizations. By drawing on the concept of an analytical decision-making culture, Popovič et al. (2012) have been able to show its relation to the use of information and its influence on content quality. Skyrius et al. (2016) emphasize the importance of identifying the factors that affect the development of a culture for BI&A, and Holsapple et al. (2014) call our attention to an analytics-friendly culture to ensure readiness for BA. Overall, these studies highlight the need for BI&A awareness and an analytical BI&A culture in general. The BI&A experts ranked these items high on their list for SMEs. However, only a few studies have focused on these concepts, and very little is currently known about an analytical BI&A culture and awareness, as most researchers have not examined these concepts in detail. There is certainly a need for future research on these topics.

Second, several experts remarked that it is important to *start small but think big, and that SMEs should build their BI&A capacity iteratively*. We therefore argue that BI&A adoption projects in SMEs should be iterative, going first for the "*low-hanging fruits"* to demonstrate proof of concept and the business value of BI&A systems. This will help maintain the organizational commitment during the implementation project. This commitment will be necessary when taking on the more challenging implementation issues, such as changes to the IT infrastructure and the organizational processes. By starting small and having a long-term perspective, major infrastructure investments can be postponed to a later stage. Instead of the use of a stage-gate approach (water-fall type) with shorter timelines in the project, iterations and long-term goals should be the focus. In this way, SMEs can build and maintain enthusiasm and top management support through the more challenging phases of IT infrastructure transformation and organizational change process, while still keeping the focus on the complete BI&A vision.

We emphasize that the organizational change capabilities in SMEs (e.g., the project champion as one important item) also affect organizational readiness. With strong organizational change capabilities, SMEs are likely to be more adaptive to changes. In the BI&A implementation, the decision-making practices within organizations must be evaluated and brought to the table, and an analytical culture and mindset must be established. Organizations seek to transform intuitive decision-making practices into fact-based and collaborative decision making by implementing BI&A systems (Habjan, Andriopoulos, & Gotsi, 2014). In addition, Frisk, Lindgren, and Mathiassen (2014) have emphasized the importance of adopting investment approaches that promote creative and adaptive decision processes, recognizing tangible as well as intangible paths to value creation. This requires the development of an IS evaluation approach that includes a multiplicity of value criteria based on previous knowledge and learning from failure - leading to a better understanding of IT investment decisions among the organizational stakeholders (Frisk, Bannister, & Lindgren, 2015). An evaluation approach will be important for SMEs, that need to learn from a gradual BI&A implementation approach. For SMEs in growth, this is important when exploring and testing different investment ideas and when conducting an appropriate evaluation of alternative extensions of solutions during the BI&A project life cycle. Utilizing high-quality information in operational decisions is crucial to achieve this (Habjan et al., 2014; Huang, Pan, & Ouyang, 2014).

Third, we find that the Soh and Markus' (1995) IS value process model is appropriate to understand BI&A adoption. We utilized this model to theorize our findings of adoption drivers and inhibitors to better understand the value creation process of BI&A in SMEs. The most popular IS adoption models such as DeLone and McLean's IS success model (Delone & McLean, 2003), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) and Technology Acceptance Model (TAM) (Davis, 1989) have been widely used to study individual users' adoption of new technology, such as BI&A (Ain et al., 2019). However, our findings show that individual user adoption of BI&A is not perceived to be important among the expert in our panel. Instead the experts focus primarily on adoption issues at the organizational level. Adoption of complex and organization-wide systems entail substantial investments, infrastructure change and organizational process changes, and will be very demanding for the organization. We argue that organizational challenges will overshadow individual user adoption issues. We therefore conjecture that analysis at the organizational level would be most appropriate for BI&A adoption research.

The experts' strong focus on organizational value and iterative stages also renders Diffusion of Innovation (DOI) theory inappropriate. A few recent studies have utilized the DOI theory as an analytical lens to explain BI&A adoption in SMEs (e.g., Popovič et al., 2018; Puklavec et al., 2014; Puklavec et al., 2018). The first shortcoming is that the DOI approach misses the iterative nature of BI&A projects. The DOI theory describes a set of distinct stages, but complex technology do not seem to diffuse in sequential stages (Lyytinen & Damsgaard, 2001). We need to see BI&A adoption as a long-term iterative project instead of a set of stage-gate (waterfall) styles of adoption, as discussed above. This means that there are critical issues related to building commitment in an iterative project and maintaining this commitment during the long-term project's lifetime. Some of the Delphi panel experts even suggested that BI&A adoption projects may go on for a very long time; there may always be new needs for changes to the BI&A system, the decision-making environment, the infrastructure, or the decision processes themselves, in accordance with technological developments and changes in the business environment.

The second shortcoming of DOI is that it misses the significance of the performance stage of the adoption. The five-stage version of DOI has a confirmation stage, in which the individual or the organization finalizes the decision to continue using the innovation. We argue that the performance stage is a more extensive phase and is not merely a confirmation that the technology works. It is also about demonstrating to the organization that the implemented technology has significant effects on competitive performance and the bottom line. The Delphi panel experts emphasized enterprise performance and competitive advantage among the drivers of BI&A adoption, and that realizing strategic value from the systems was important for the further adoption and implementation of advanced BI&A systems. We argue that DOI should be amended with a performance stage and iterations between the stages to account for the iterative building of organizational acceptance and resource allocations.

Fourth, we have demonstrated the utility of a grounded Delphi approach. By following up a ranking type Delphi method with interviews of several panelists, we were able to achieve a deeper understanding of BI&A adoption in SMEs. This combination provides a richer understanding of the topic under investigation by identifying core themes and their interrelationships. First, the panelists identified the most important drivers and inhibitors of BI&A adoption in SMEs, and the experts ranked the items to determine relative importance and to gradually achieve group consensus. We further analyzed the topics to define the core concepts at a higher level of abstraction (figure 2 and 3) to understand how the core categories influence adoption. We recommend this combination of Delphi approaches for future studies that seek abstraction of core concepts to understand how and why main themes are connected.

Fifth, we also provide some recommendations for practice. We have identified several recommendations based on the identified inhibitors and the discussion above. Our study identified several technological drivers such as data management (including driver 7; data quality) and information and reporting. However, creating an efficient organizational data environment with high data and information quality is challenging. For organizations to change decision-making processes and improve analytical capabilities, we recommend that they focus on building information management capabilities and analytical skills. This is important to enhance the quality of information in strategic decision-making processes. This capability is also related to ensuring the efficient integration of systems, as well as the utilization of software that can extract quality information. Previous research indicates that information management capability is an important moderator for achieving firm performance (Habjan et al., 2014). Moreover, both information access and information content quality, as well as analytical capabilities, are considered crucial constructs to obtain success with BI&A solutions (Popovič et al., 2012). In our study, this relates to the development of organizational change capabilities, that lead to higher readiness. We therefore recommend that SMEs pay attention to change management and to building an analytical culture with a specific focus on the decision environment, as well as to developing their information management capabilities. The set of recommendations is presented in Table 4.

Table 4. Key recommendations for decision makers and managers adopting BI&A

Concept	Recommendations for decision makers and managers
Organizational data environment	• BI&A needs to be an executive priority. • Start small, think big. • Investments in competencies and solutions should materialize gradually. - Go for the low-hanging fruits; demonstrate proof of concept and business value. - Implement infrastructure gradually. - Think of the long-term life cycle project with iterations; avoid a stage-gate mindset in the project. - Utilize a problem-driven data collection strategy; avoid a comprehensive data collection strategy and data warehouse. - Build information management capabilities, identify the most important information for decisions, and evaluate information quality.
BI&A market challenges	• BI&A adopters should invest in simple BI&A solutions with low investment costs. • BI&A adopters should consider functional BI&A systems as a point of departure and reflect on possibilities for cloud computing solutions.
Organizational readiness	• BI&A needs to be an executive priority. • BI&A adopters in SMEs need to tackle resource poverty and the limitation of technological and human resources. - Be aware that technical capabilities are important, but, do a careful prioritization and selection of which technological capabilities should be developed. - Focus on the building of the IT competencies needed. - Focus on human resources, and, if possible, establish a small BI&A team and/or select a project champion. - Allocate as much resources as possible within limitations to necessary training and to incentives for the project champion. - Focus on the creation of BI&A awareness, consider the socio-cultural environment, and resolve any cultural issues. • Evaluate the analytical BI&A culture. - Is the decision culture based on intuition? Is it rational? - Focus on the fact-based decision-making environment. - Focus on a collaborative decision-making environment that includes key stakeholders, thus allowing multiple perspectives. - Focus on both internal and external factors that influence company growth from the BI&A (e.g., business excellence and customer excellence).
Organizational change capabilities	• BI&A adopters should establish a change management strategy across the organization to ensure commitment to BI&A adoption initiatives. • BI&A adopters should establish the following change management initiatives during the project: - Enable BI&A awareness in terms of communication and training for all decision takers in the organization - Focus on *soft* infrastructure—organizational culture, skills, and motivation
Legal requirements	• BI&A adopters need to build the necessary competencies in privacy and security regulations and implement these as a part of the BI&A approach. • Security issues must be taken seriously to ensure safeguarded access to critical internal and external information sources; system privileges should be carefully decided upon and set up.

7 Conclusion

BI&A and related technologies are considered among the most influential IT investments in enterprises, and accordingly, research interest in them has increased. The purpose of this study was to provide a deeper understanding of BI&A adoption in SMEs. A ranking-type Delphi study was undertaken, and 39 BI&A experts in a panel identified and ranked the most important drivers and inhibitors of adoption. Follow-up interviews were conducted to explore how these factors influence adoption.

This study makes five main contributions to theory and practice. First, this study contributes to the IT/IS adoption literature. It expands our understanding of BI&A adoption in SMEs and provides a deeper insight into the drivers and inhibitors influencing the value creation process. Research on SMEs is imperative since they constitute more than 99% of enterprises in developed countries. Therefore, studies of IS adoption need to take SMEs characteristics into account to be generalizable to enterprises in general. The empirical findings extend our understanding of organizational readiness in order to understand adoption. Second, the study adds to the growing body of research on business analytics and decision environments in organizations by shedding light on the SME context. Third, the proposed recommendations have practical implications and will be of interest to decision makers in organizations investing in BI&A solutions. Fourth, we demonstrate that the IS value model proposed by Soh and Markus (1995) is appropriate to theorize the value creation process for SMEs adopting BI&A by linking the identified core drivers and inhibitors to different steps of this model. We put forward that the most popular IS adoption models and the diffusion of innovation theory all have limited applicability.

Finally, we make a methodological contribution by combining a ranking-type Delphi study with a grounded Delphi approach. The grounded approach provided further theorizing and revealed the interrelationships between core categories of drivers and inhibitors. This combination provided a richer understanding of BI&A adoption, and it demonstrated the value of a grounded Delphi approach for achieving a deeper understanding of a complex issue.

This study has limitations, and several questions remain to be answered in future research. Further investigation is needed into the role of an analytical culture in the decision-making environments of SMEs. A better understanding should be gained from longitudinal studies, examining adoption processes over time by focusing on BI&A life cycles in SMEs, value creation, and organizational performance. Finally, quantitative studies are required to test the relationships between organizational readiness and other influencing factors and capabilities.

Appendix

Table A1. BI&A adoption drivers (brainstormed) organized into TOE categories. The top 18 drivers from the final ranking are marked

TOE	Drivers	Explanation	Ranked item
Technological	The need for a deeper data insight	➢ The need to gain more insight into internal data (revenue, cost, profitability, customers, etc.) ➢ The need to get useful data from several operational or administrative systems, and business rules involved. To provide bases for comparison ➢ The need to understand the total picture of the business	1
	The need for data integration	➢ The need to consolidate data from disparate sources/systems ➢ The need to integrate information from different departments, business components, and so on ➢ The need to combine information with other types of data for analysis and correlation	3
	The desire for data quality and structure	➢ The need to take control of data quality to ensure that reporting is consistent throughout the company ➢ The desire to focus on data quality content. Trust in any system is dependent on good data quality and structure ➢ Good data quality and structure are important for developing proficient solutions	7
	The need for data visualization	➢ The need for tools that provide out-of-the-box graphical techniques, which are easy to apply on quantitative data	16
	The need for updated and accurate information	➢ The need for assembling fact-based and reliable information	12
	Standardization	➢ The need to standardize information, analyses, predictions and reports	-
	To extend existing solutions (e.g., ERP, CRM, MS Excel) with BI&A capabilities	➢ The need for better BI&A capabilities, since many ERP and CRM systems have limited analytical functionality ➢ The need for a better solution and to have something more robust than what the Excel application provides	-
	The need for a single version of the truth	➢ The need for having consistent reports across the organization	6
	Information overflow leads to a need for BI&A.	➢ The need for a BI&A solution to extract the most important information	-
	The emergence of the Internet of things (IoT)	➢ The need to analyze data from the IoT for better performance optimization	-
	User-friendly BI&A tools	➢ The desire to take advantage of easy-to-use BI&A tools available in the market	-
Organizational	BI&A is an executive priority	➢ Executive support is crucial for BI&A projects	10
	Knowledge and experience in BI&A tools and products	➢ Knowledgeable employees become internal BI&A sponsors	-
	The need to improve organizational efficiency	➢ The need for improving organizational processes; core, support and management processes	2
	The desire to become a data-driven organization	➢ The need to make information available to everyone ➢ The need to remove data silos ➢ The desire to improve the quality of decisions; based on facts, not gut feelings ➢ The desire to improve and speed up decision making processes	5
	The need to create better/intelligent products and services	➢ The need to create better and improved products, as well as enhance productivity, supply chain operations, and marketing ➢ The desire to embed BI&A in customer offerings to make intelligent products ➢ The desire to improve insight in order to drive strategy processes and product development. This can be derived from customer behavior overviews, support calls, and other touchpoints	-

TOE	Drivers	Explanation	Ranked item
Organizational	The need to achieve a richer reporting capacity	➢ The need to achieve an efficient and improved reporting ➢ The need for flexibility in reporting and analytics	-
	The need to automate data management and reporting	➢ The need to automate manual reporting procedures and free up resources from report creation/analysis in order to focus on interpreting the data ➢ The need to automate report production and to reduce costs ➢ The need to reduce manual data processing and avoid errors in manual reporting	11
	BI&A awareness	➢ Awareness of BI&A capabilities in the organization is a driver for initiating BI&A adoption processes	-
	BI&A champion	➢ Having a BI&A champion is important to raise commitment and enthusiasm for a BI&A project	-
	The desire to increase profitability	➢ The desire to focus primarily on profitable products, services, and outlets ➢ The need for reducing cost ➢ The need for adding business value and new product sales	14
	Risk mitigation	➢ The need for using BI&A tools to enhance risk management	-
	The desire to improve performance management	➢ The desire to measure and manage the performance of organizations ➢ The importance of having control on profit and loss in all departments	15
	The need for internal control in the organization	➢ The need for internal control and guided analytics to drive the entire company in the same direction ➢ The need for better control of KPIs for the business	-
	The need to increase competitive advantage	➢ The need for increasing competitive power and enhancing sustainable competitive advantage	9
	The desire to improve enterprise performance	➢ The need to have a better overview of the business, to identify business value, and to easily penetrate markets ➢ The need to understand business strengths and weaknesses ➢ The need to identify sales channels, products, and strategies ➢ The need to improve market insight and to discover market trends ➢ The desire to obtain foresight—the need to predict the future in order to take appropriate action (revenue, costs, customer churn) ➢ The need for identifying business value, productivity, and sales ➢ The need to increase the business and market share by identifying growth opportunities	4
	The need to achieve effective decision making at all levels of the organization	➢ The need to make better and informed business decisions in a timely fashion ➢ The desire to drive new arenas for decision making, particularly the operational focus aligned with strategy	8
	The desire to achieve customer service excellence and customer insight	➢ The desire to increase customer satisfaction, reduce/identify churn probability, and improve customer retention ➢ The desire for making product reports to the customers ➢ The need to know what the customer says, use customer insight to increase sales	13
	Owner demand	➢ The need to follow up on requirements from the owner	-
	BI&A is a priority within the organization.	➢ BI&A is prioritized and gets resource allocation	-
	The desire to keep up with technology improvements	➢ The desire to keep track of new technology improvements	-
	The desire to be perceived as an advanced technology user	➢ The desire for having a reputation of being an early adopter of new technology	-
Environmental	Legal compliance	➢ Legal compliance is critical to business. Companies can be shut down if they neglect reporting ➢ The need for mandatory reporting to the government, especially in the finance industry	17
	Change in the competitive landscape	➢ The desire to get a stronger competitive position in the marketplace ➢ The desire to differentiate from competitors	-
	Decreasing the BI&A technology cost	➢ Price is important when it comes to the decision on whether one wants to implement a BI&A solution ➢ Traditional BI&A tools are often expensive and require significant resources to be set up ➢ Cheaper BI&A technology is now available	-

TOE	Drivers	Explanation	Ranked item
Environmental	Success stories of other enterprises	➢ Success stories of companies that have implemented BI&A are important to inform other companies about the benefits of these solutions	-
	Market hype	➢ The desire to follow market trends; companies are afraid of falling behind ➢ Companies can be influenced by market hypes such as cloud computing, open source, and data science	-
	Emergence of the General Data Protection Regulation (GDPR)	➢ This will increase the demand for BI&A. BI&A consultancy companies are concerned with GDPR, which is good news for further development of BI&A solutions	18

Table A2. BI&A adoption inhibitors (brainstormed) organized into TOE categories. The top 18 inhibitors from the final ranking are marked

	Inhibitors	Explanation	Ranked item
Technological	Data security concerns	➢ The concerns about who within the organization will be able to access critical or sensitive information	8
	BI&A project complexity	➢ BI&A projects are complex and require much time resources for the implementation ➢ BI&A projects may lead to endless stream of changes during implementation	7
	Poor data quality	➢ Poor data quality will provide limited value of BI&A solutions ➢ Without good data quality, the trust in BI&A will suffer and decision making could be done based on false premises	4
	Difficulty in selecting the appropriate BI&A tools	➢ Difficulty in finding the right software ➢ Using or have implemented inappropriate BI&A tools	-
	BI&A tools complexity	➢ Interface complexity of BI&A tools ➢ BI&A technology is too difficult to learn	-
Organizational	Limited resources	➢ SMEs lack financial strength and have tight budgets. ➢ Lack of sponsors who have the money for BI&A implementation	2
	Lack of knowledge about BI&A tools and products	➢ SMEs do not know how to utilize the tool and do not understand why they need it ➢ No general overview of BI&A solutions and their benefits ➢ Lack of experience and an understanding of BI&A possibilities	11
	Lack of technology competence	➢ Lack of IT competence in SMEs is challenging for the adoption of new tools ➢ Technology competence is required for BI&A implementation ➢ A small business is likely to have commodity software installed that may be difficult to integrate with the BI&A solution	14
	Lack of BI&A competence/skills	➢ BI&A competence and skills are important for maintaining BI&A solutions ➢ Usually, SMEs have a shortage in people, including people with BI&A skills ➢ Low internal BI&A competence and skills in SMEs ➢ Lack of an internal BI&A community in SMEs	1
	Lack of BI&A awareness	➢ Not being aware of BI&A possibilities and not recognizing the value of BI&A ➢ Not being aware of the existence of BI&A solutions	5
	Difficulty in realizing the benefits of BI&A	➢ No understanding of the real benefits of BI&A ➢ Spending too much resources before results and benefits are seen	-
	BI&A is not an executive priority.	➢ Lack of top management support will create obstacles for starting a BI&A project	13
	Implementation time requirements	➢ Lack of resources can be an inhibitor; for example, to allocate enough time for execution and enough time for the organization to assess the solution ➢ Lack of time required for training the employees	17
	Technophobia	➢ The managers do not trust the system and are afraid of losing control ➢ The managers are skeptic to new IT investments in general	-
	Resistance to change	➢ Employees want to keep old habits and are resistant to changes ➢ Changing users' mindset can be difficult	9
	BI&A requires organizational change	➢ Adopting BI&A tools requires a significant amount of change in how the organization uses and acquires information	15
	BI&A is not a business priority.	➢ BI&A is not the top priority of smaller companies ➢ Small companies have little data and few systems, making BI&A appear less relevant	-
	Difficulty in building effective use cases	➢ Lack of knowledge on how to achieve the return of investments (ROI) or how to develop use cases	-

	Inhibitors	Explanation	Ranked item
Organizational	Lack of an analytical culture	➢ No culture for utilizing fact-based information to make decisions, no culture for developing high quality content of information to make decision ➢ Decisions are taken mostly based on intuition and gut feelings	10
	Lack of a BI&A champion	➢ Lack of a champion who can push the project to completion ➢ Lack of a champion who have the drive for BI&A	6
	Data sharing and access issues	➢ Unwillingness to share data across departments and among employees ➢ There may be perceptions such as: "These are our data. Does anybody else need our data?"	-
	SMEs' volume of data is too small, and business cases are few	➢ SMEs might have little data; this makes BI&A appear less relevant	-
	Internal competition for resources	➢ Competition about resources between different projects and departments. This can lead to low prioritization of BI&A projects	16
	Perceptions of BI&A as a backward-looking technology	➢ The perception that BI&A is based on information from yesterday and not on future impacts. The organization may ignore important internal/external influences that can have an impact on the business ➢ The perception of creativity in the organization can be undermined, since BI&A can focus too little on current information	-
	BI&A project scope creep	➢ Many BI&A projects want to encompass too many KPIs, measures, and report requirements ➢ BI&A projects become too extensive	18
	Organizational power mechanisms	➢ Politics regarding technology adoption decisions may inhibit BI&A investment decisions ➢ Company power structures and politics can influence the adoption negatively	-
Environmental	Risk for failure	➢ High risks of failure ➢ Bad reputation of BI&A solutions ➢ Few success stories	-
	Cost of BI&A tools and consulting	➢ Upfront setup, running, and maintenance costs are high ➢ BI&A project implementation, operational and training costs are high	3
	BI&A vendors have business models that are not tailored for small accounts	➢ The vendors typically focus on large customers, affecting the pricing and complexity of BI&A solutions	12

Table B1. Reasons for selecting the top drivers

TOE	Driver	SME relevance	Reason for its importance and sample quotes
T	The need for a deeper data insight	---	It is important to understand the kind of data available, how organizational data are assembled from operational and administrative systems, and insights about internal data. *"BI is all about insight, a deeper insight into the business data, I think it is obvious that this is the general driver."* *"Data insights are important because you will always want to make your decisions based on fact, with a hint of gut feeling, and not the other way around."*
O	The need to improve organizational efficiency	---	It is related to a deeper data insight. It is important to have this insight to increase efficiency and effectiveness in business processes. It is about the need to improve decision making in order to increase revenue, reduce costs and increase quality. *"Reducing cost and improving quality are the two major drivers for improving organizational efficiency. […] So, you need insight to see where you can improve efficiency."* *"You can identify bottlenecks to improve the purchase process. You can also use your data to build automated processes with algorithms that use data as input to make automated decisions. And this is how you achieve reduced costs and better-quality service that leads to improved organizational efficiency".*
T	The need for data integration	---	Being able to consolidate data from disparate sources across departments and get a holistic picture is important to comply with business demands regarding data availability. *"The most difficult part of creating insight is integrating your data so that you get a holistic picture, and to do that, you need to integrate data from several systems. So, in this sense, data integration will always be an important part of BI."* *"The need for data integration is one of the most important issues in a technical sense. But this is not a business project but an IT project. The business demands data availability not only for BI analytics and reporting, but also if the marketing department buys a new SaaS solution that needs qualified data."*

TOE	Driver	SME relevance	Reason for its importance and sample quotes
O	The desire to improve enterprise performance	---	Superior performance in the marketplace is dependent upon advanced analytical capabilities. *"We have so many possibilities with the massive volume and diversity of data available to us. With these data we can do more automation and build smarter algorithms to achieve improved organizational performance."* *"The use of BI is to measure and manage performance […] that includes benchmarks for internal incentive models, bonuses, benchmarks of competitors, and balanced scorecards with both leading and lagging indicators."*
O	The desire to become a data-driven organization	---	This is important because of the increased focus on digitalization in order to stay competitive. Given the importance of automation and working smarter, business processes are becoming more and more data driven. *"Most companies need to digitalize and automate as much as possible in order to stay competitive. And that is only possible when you become data-driven, meaning that business processes are more or less driven by your data."* *"[…] to achieve intelligent automation, you need to be data-driven. So, to become data-driven you basically need a lot of data and insight to automate things."*
T	The need for a single version of the truth	---	It is important to standardize the collection and usage of data, as well as to have common business rules and conformant business data in all reports. *"[…] core business data needs to be conformant and give the same results across different reports. If the core business data differs across reports, decision makers may lose trust in the BI solution and stop using it, and they may even go back to making decisions based on gut feeling instead of facts. That's probably why many BI experts in your study considered a single version of the truth to be a [crucial] driver."*
T	The desire for data quality and structure	---	BI&A can combine unstructured data from many different sources. This is a challenge for conducting proper analysis; the data obtained need to have a certain quality that is different from the source data. *"BI is usually about querying huge amounts of data in the same operation, and that requires a different structure. Also, the people operating the transactional systems are usually focused on the operational processes they support and may not have the same focus on keeping the data complete and conform. This creates data quality issues from an analyst's point of view."* *"Analysts and decision makers usually need more structured, conformed and enriched data compared with the users of a specific system that contains [one type] of source data."*
O	The need to achieve effective decision making at all levels of the organization	---	It is important to have access to core business data for decision making at all organizational levels. *"The core business data are needed by all decision makers, and BI provides this information. This is more efficient than all decision makers making their own reports and analyses from scratch. BI solutions are flexible for exploring data based on different perspectives–to do slice and dice."*
O	The need to increase competitive advantage	---	BI&A can support organizations in predicting market trends which is important to stay competitive. "*It is very important to collect and analyze data in order to stay competitive. It is a certainty that companies focusing on fact-based decision processes are more profitable than average companies."*
O	BI&A as an executive priority	---	BI&A is a costly and comprehensive investment in SMEs, it requires consistent and strong support from top management. *"If management says they need a BI solution, that's when you know your project will be a success."*
O	The need to automate data management and reporting.	---	BI&A reduces manual data processing. The focus is on interpretation and data analysis.
T	The need for updated and accurate information	---	BI&A can provide more accurate analysis. To focus on fact-based decision processes are important. Competitive advantage will depend upon BI&A maturity in the organization. *"It's very important to collect and analyze data in order to stay competitive. It is a certainty that companies focusing on fact-based decision processes are more profitable than average companies." "With more structured data you're able to do a more accurate analysis. But [competitive advantage] is very much dependent on the BI maturity of the company."*
O	The desire to achieve customer service excellence and customer insight	---	BI&A allows companies to get a more complete visualization of customers. BI&A helps an organization to target the right market segment. *"The most important perspective is usually the customer perspective, recruiting new customers, reducing churn, and keeping the most valuable customers. Through BI adoption, […] even small companies can achieve these benefits."* Social media has become important, and the need to interpret social media data is urgent to understand customers and market trends.

TOE	Driver	SME relevance	Reason for its importance and sample quotes
			"[The analysis of] social media has tremendously enhanced the way organizations identify and understand the target markets."
O	The desire to increase profitability	---	BI&A supports SMEs in increasing efficiency and effectiveness, and impact of BI&A is cost reduction and increased profitability.
O	The desire to improve performance management	---	BI&A offers necessary tools to improve performance management.
T	The need for data visualization	---	BI&A supports distribution of reports and visualize the data in a better way.
E	Legal compliance	---	BI&A provides the means to comply with reporting obligations to governmental authorities. *"When it comes to reporting like that, it is very dependent on the type of business; for example, in banks, there's a lot of [mandatory] reporting to do. And BI is a good way to standardize according to regulations."*
E	Emergence of the General Data Protection Regulation (GDPR)	---	GDPR is important for organizations that have many external customers (e.g., retailers). *"GDPR is more about how to protect the data […] if you have many individuals accessing data from everywhere [causing a reduction in security], which is what you will do if you don't have BI. BI can help with this matter [GDPR]."*

Table B2. Reasons for selecting the top inhibitors

TOE	Inhibitor	SME relevance	Reason for its importance and sample quotes
O	Lack of BI&A competence/ skills	✓	It is rare to find BI competence in SMEs. Lacking internal competence, SMEs need to rely on external competence. External consultants do not know business processes well enough. *"[SMEs lacks internal BI competence, while] …external consultants do not have the same insight into the organization and do not understand the internal business processes and technology. And this can lead to more time and effort in developing the specification, as well as a longer implementation period."*
O	Limited resources	✓	SMEs have limited resources compared with larger companies. They have tight budgets and cannot afford to have their own BI&A teams. *"When small companies have tight budgets, they cannot afford a big team of BI participants or data scientists. They will be dependent on finding multi-skilled, flexible, and adaptable resources."*
E	Cost of BI&A tools and consulting	✓	SMEs lack BI&A skills, and need to rely on external resources in order to implement BI&A. This makes the project expensive. It is also challenging to select external consultants and solutions because of the lack of BI&A skills. The projects last very long and external resources are needed for a long-term perspective. *"Using consultants for this development gets costly, and this kind of investment might be considered too high for SMEs."*
T	Poor data quality	---	Poor data quality leads to a lack of trust in the BI&A system. Reporting and analytics have different data quality requirements compared with operational IS. This makes it difficult to move forward with BI&A. *"Poor data quality is one of the issues in a BI project [that must be addressed in the BI&A project]. If you have poor data quality [after BI&A is implemented], you haven't done the project correctly."*
O	Lack of BI&A awareness	✓	It relates to the lack of BI competence/skills. Low competence leads to low BI&A awareness. Compared with larger companies, SMEs have limited experience with utilizing large volumes of data. There are few success stories that SMEs can refer to. *"The lack of BI competence and skills also means less awareness in the organization–less knowledge about what is possible to achieve, how it could be achieved, and the outcome of the potential benefits."* *"Whereas large enterprises have been troubled with large volumes of data, many data sources, and complex integrations for years, small companies might have only recently started to experience the issue of gaining insight into fast–growing data complexity. This is a significant inhibitor of BI adoption in smaller companies."*

TOE	Inhibitor	SME relevance	Reason for its importance and sample quotes
O	Lack of a BI&A champion	---	It is important to have a champion to create enthusiasm for the BI&A project. The lack of a champion can lead to an unsuccessful project. It is also an important success criterion. The champion should ensure IT and business coordination. *"The lack of a champion will only be visible after the project has started, and yes, it's an important inhibitor. If you don't have the enthusiasm for it, your project will fail. And you don't need only one champion; the organization itself needs enthusiasm."* *"Having a BI champion is a success factor. It's always positive in any initiative to have a very skilled person who takes the lead."*
T	BI&A project complexity	---	There are concerns about changes that occur in BI&A projects, data from many different systems make the project comprehensive and difficult to tackle. "*In projects I've worked with there seems to be an endless stream of changes [...]. This has a major effect on any BI initiative and may be destroying the solution. Such changes are hard to plan for and it can be argued that any BI solution can be THE system that makes such changes possible."* *"Start slow, build brick by brick, and never ever go for a big bang project."*
T	Data security concerns	---	There are concerns regarding who should have access to the data in a BI&A system. BI&A provides easy access to core business data in a compressed form.
O	Resistance to change	---	This can create problems if the BI&A project aims to automate, and employees fear losing control and power. Not all employees want a single version of the truth. *"There might be some job protection instinct when the idea of BI is introduced in the context of automation, and it implies staff reduction."* *"When the BI team proposes to create a 'single version of the truth' this might not be of interest to all parties. This is because some employees are afraid of losing control or power."*
O	Lack of an analytical culture	✓	SMEs have limited resources (compared with larger enterprises) and have not developed a strong analytical culture. Decisions tend to be taken on gut feelings. *"The lack of an analytical culture is an obstacle, and small businesses are transparent. They have few employees, and everyone knows what other colleagues are doing. They may think that they do not need to analyze the data because they already have an overview."*
O	Lack of knowledge about BI&A tools and products	✓	SMEs do not have much knowledge about how to utilize BI tools.
E	BI&A vendors have business models that are not tailored for small accounts	✓	Traditionally, BI&A business models have targeted large customer companies. Therefore, BI&A investments have been costly and unattractive for SMEs. *"It used to be a big issue back in time, but now, I see a lot of companies offering BI solutions that are quite cheap. Of course, you still have very expensive companies like nn [large consultancy company], but you have more open source tools now, and you have some other tools that are becoming very cheap that smaller companies can invest in."*
O	BI&A is not an executive priority	✓	If top management does not clearly prioritize a BI&A project, it will not get necessary commitment in the organization. This is especially critical for SMEs. *"In some organizations you will still find top management that has little interest in changing the way reporting is done. They do not possess the skills of the BI project team and may be resistant."*
O	Lack of technological competence	✓	Typical for SMEs, this relates to the first and second organizational inhibitors.
O	BI&A requires organizational change	✓	Adopting BI&A will require a change in the organization regarding the use and acquisition of information. This is also related to *resistance to change* and *internal competition for resources*.
O	Internal competition for resources	✓	BI&A projects are costly and require external competencies. It is also costly because of back-end tools, ETL and data integration tools. This can cause competition about resources internally, and other pressing initiatives can create difficulties in getting commitment for a BI&A initiative.
O	Implementation time requirements	✓	BI&A projects take time because of their complexity. *"If your project does not deliver results through a milestone plan, no one will know what you are doing, and the credibility of your project will suffer. And when you have no credibility left, the funding will stop as well."*
T	BI&A project scope creep	✓	Often BI&A projects become more complex than expected. This is especially a problem for SMEs with a low BI&A experience. *"BI requirements tend to change when the users start getting insights. This might be considered as scope creep for project leaders and budget owners."* *"This inhibitor is a result of bad project planning, and it is important to focus on a 'start small, think big strategy' when embarking on a BI project."*

✓ Especially relevant for SMEs (usually not typical for larger companies, but, in some cases, larger companies might have similar issues)
--- Independent of company context, can be relevant for both SMEs and larger companies

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