International Journal of Information Management 46 (2019) 93–103

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Business intelligence and analytics for value creation: The role of absorptive capacity

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ARTICLE INFO

Keywords:
Business intelligence and analytics
Value
Insights
Absorptive capacity
Assets

ABSTRACT

Firms continuously report increased competitive value gains from the use of business intelligence and analytics (BI&A), however, little is known about how insights from BI&A are transformed to added value to date. We have conducted fourteen in-depth, semi-structured interviews with a sample of informants in CEO positions, IT managers, CIO, Heads of R&D, as well as Market Managers from nine medium or large-sized European firms. Applying the absorptive capacity's theoretical lens, we have provided evidence that absorptive capacity's capabilities are an underlying foundation in the process of transforming BI&A triggered insights into valuable knowledge. Moreover, this process is supported by technological, human, and relationship assets.

1. Introduction

The amount of data and information generated on a daily basis continuously increases, forcing firms to increasingly rely on external knowledge and information to enhance firm innovation and performance (Benner & Tushman, 2015; Ireland, Hitt, & Vaidyanath, 2002). With the quick development of computer intelligence as well as the appearance of "big data" concept, business intelligence and analytics has become an increasingly important concept for researchers and practitioners (Chen, Chiang, & Storey, 2012). Although BI&A were initially used for decision-making support activities, they have been increasingly considered for organizational learning and adjustments, improving operational efficiency, and strengthening organizational intelligence (Trieu, 2017). A survey conducted by IBM Institute for Business Value and MIT Sloan Management Review reported that firms are increasingly gaining competitive advantage from analytics (58% of the more than 4500 respondents reported competitive value gains from analytics) (Kiron & Shockley, 2011). Not surprisingly, Gartner's survey on IT Spending found BI&A to be a top priority for most of the analyzed firms and predicted that BI&A would remain one of the top foci for the leading firms (Gartner, 2013).

On the other hand, firms have acknowledged the potential of BI&A to generate insights and knowledge from both external and internal sources of knowledge (Shehzad, Khan, & Naeem, 2013; Wang, 2014; Wixom, Watson, & Werner, 2011; Yeoh & Koronios, 2010). As the complexity of the data is increasing, humans have difficulties interpreting the external information due to limited mental capacities (Jansen, Van Den Bosch, & Volberda, 2005; Sammut & Sartawi, 2012). More information is not necessarily beneficial for the organization since its information and knowledge processing capacity is limited as well (Simsek, 2009). As a result, organizations develop information filters and routines to cope with bounded rationality (March, 1978; Nelson & Winter, 1982). BI&A have found it possible to expand the human mental capacity as well as the firm's absorptive capacity by increasing the ability of individuals and firms to receive, store, analyze and transfer information with fewer errors (Brynjolfsson & Hitt, 2000; Elbashir, Collier, Sutton, Davern, & Leech, 2013; Simon, 1991). While various streams of studies have provided research on the BI&A potential, there has been little attention given to the improvement of understanding the role of BI&A in the process of knowledge generation from external data and with it, the underlying mechanisms that facilitate this process.

Despite the prominence of BI&A as a source of competitive advantage with an abundance of studies acknowledging the ability of BI&A to derive business value, anecdotal evidence has been made to capture the BI&A value creation process (Chen, Preston, & Swink, 2015; Fink, Yogev, & Even, 2017; Trieu, 2017; Vidgen, Shaw, & Grant, 2017). Prior research in the information systems (IS) research field has examined the role of BI&A for insight generation; however, predominantly from the technological aspect (Bose, 2009; Chaudhuri, Dayal, & Narasayya, 2011; Ranjan, 2009). Only a few studies have investigated the role of BI&A from an organizational aspect; such as, organizational learning, organizational capabilities, effective use, and customer relationship management (Elbashir, Collier, & Sutton, 2011,

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https://doi.org/10.1016/j.ijinfomgt.2018.11.020
Received 22 February 2018; Received in revised form 24 November 2018; Accepted 30 November 2018

2013; Forsgren & Sabherwal, 2015; Real, Roldán, & Leal, 2014; Trieu, 2017; Yeoh & Popovič, 2016). Despite the strong technological focus, valuable customer insights are usually a result of a meaningful transformation of BI&A insights into meaningful knowledge that is subsequently dispersed across business units to be acted upon (Fan, Lau, & Zhao, 2015; Shollo & Galliers, 2016).

Ergo, more recent studies (Fink et al., 2017; Shollo & Galliers, 2016) have criticized overemphasizing technology without accounting for the human 'sense-making' processes. As Sharma, Mithas, and Kankanhalli, 2014, p. 435) "insights emerge out of an active process of engagement between analysts and business managers using the data and analytic tools to uncover new knowledge." Accordingly, Shollo and Galliers (2016) have provided empirical evidence of the BI&A agency in data selection and problem articulation for the active process of knowing. Moreover, Fink et al. (2017) have presented and empirically tested a model of BI& value creation which identified BI team and infrastructure assets that were transformed through operational and strategic BI capabilities into operational and strategic value; a process moderated by exploitative and explorative learning. Although they attempted to theoretically advance the BI&A research through the lens of organizational learning, they offered a limited understanding of the underlying processes, therefore, calling for further research to strengthen the theoretical foundation of BI&A research. Moreover, as Trieu (2017) noted in his most recent, exhaustive literature review study, there is a lack of research that studies the complementary links between BI impacts and organizational BI assets to help the organization better understand the value creation process, and has suggested applying an inductive inquiry approach to explore this complex phenomenon. Extending the discourse, we seek to answer the following research question*: "How are BI &A triggered insights transformed into valuable knowledge?*

To address this research question, we have conducted qualitative research involving fourteen key informant interviews in nine European firms. Following Trieu's (2017) recent findings, we consider the existing absorptive capacity's theoretical lens as a sensing device to analyze empirical data. Although concepts such as absorptive capacity capability have been used in prior studies (e.g., Elbashir et al., 2011; Ramamurthy, Sen, & Sinha, 2008; Trieu, 2017), it has remained unclear how the underlying capabilities and resources contribute to business value creation. Using the abductive method of inquiry, we have attempted to elaborate on existing theories, focusing on the role of BI&A in the organizational knowing processes and its underlying capabilities and assets which facilitate value generation process. This includes but is unrestrained to decision-making.

Our research identified the role of the four absorptive capacity's capabilities in insight generation and exploitation. Secondly, we studied the assets needed to allow full realization of the identified absorptive capacity capabilities. Our findings suggest that absorptive capacity allows external business insights from BI&A to be successfully assimilated and transformed into valuable business knowledge. Internal human, technological, and relationship resources have appeared to be the prerequisites necessary for the insights transformation process. A better understanding of the former has contributed to previous IS and management research. Also, practitioners can benefit from a comprehensive overview of the capabilities and resources needed to turn BI&A insight into meaningful actions and decisions, allowing them to adjust their efforts accordingly. Therefore, we offer a holistic and systematic understanding of the underlying capabilities and the underpinning assets that allow knowledge extraction from BI&A insights.

The remainder of this paper is structured as follow. In the first section, we review the concept of BI&A and the absorptive capacity theory. In the second section, we present the research context and the methodology, followed by the overview of findings. The last section concludes with a discussion of the findings, implications for theory and practice, and limitations and further research suggestions.

2. Literature review

This section offers a review of the current literature revolving around the BI&A value creation process; focusing primarily on the organizational impacts that result from BI&A use. Next, we present the Absorptive Capacity Theory and discuss the resources necessary for the full realization of the absorptive capacity capability.

2.1. BI&A definition

Existing literature offers several definitions of BI&A, none of which has been well-accepted. Namely, from the first appearance of Luhn (1958) the BI&A term was most commonly used to describe systematic processes (Lonnqvist & Pirttimaki, 2006), methodologies (Ranjan, 2009), technologies (Bose, 2009; Kimball & Ross, 2011), analytical tools (Davenport & Harris, 2007; Elbashir, Collier, & Davern, 2008; Watson & Wixom, 2007), and techniques (Lim & Lee, 2010) that use computer-supported systems to collect, analyze, and disseminate information for effective business activities and better decision-making. The current, most widely used definition is Chen et al. (2012), p. 1166) encompassing definition that covers most of the existing literature perspectives and refers to BI&A as "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions". This perspective diversely leads to different aspects of the value creation process. Thus, a literature review is required to define the current study and determine what we already know about the BI&A value creation process.

2.2. BI&A value creation process: A literature review

Recent academic and practitioner literature emphasize the ability of organizations to create value through the use of BI&A (Chen et al., 2012; Larson & Chang, 2016; Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013). For instance, Lavalle et al. (2011) found top-performing organizations to have substantial experience using BI&A to create value. Similarly, Chen et al. (2012) have recognized the role of BI&A in acquiring intelligence on customer needs and opinions, leading to new business opportunities. Despite increased interest, the process of transforming the insights triggered by BI&A into valuable business knowledge remains vague. Thereby causing many authors such as Sharma et al. (2014) and Ross, Beath, and Quaadgras, (2013) to call for a deeper analysis of how organizations can create value from the use of BI&A and understand the underlying resource allocation processes.

Over the past decade, a widespread interest of researchers and academia have stimulated a remarkable body of research to determine the added value of investing in BI&A technology. Many studies are contributing to this knowledge in different ways. A general presumption from the extant literature is that BI&A use leads to improved efficiency for the decision-making process. Thus, a common premise of this view is that BI&A allow identification, capture, and production of new insights and knowledge, later used for decision-making (Acharya, Singh, Pereira, & Singh, 2018; Hou, 2012; Kowalczyk, Buxmann, & Besier, 2013). For instance, Popovič, Turk, and Jaklič, (2010) proposed a research model for deriving business value from BI&A and found BI&A maturity and absorbable capabilities to facilitate the use of quality information enabled by BI&A in business processes and decision-making. Similarly, Elbashir et al. (2008) in their survey-based study, found BI&A to deliver value through improved business processes (business partner relations, internal process efficiency, and customer intelligence benefits). Trkman, McCormack, De Oliveira, and Ladeira, (2010) found firms that support analytical capabilities with good IS to perform better in delivering decisions. Furthermore, IşıK, Jones, and Sidorova, (2013) empirically found the importance of technological capabilities and high-quality data to support decision-making and accessibility to all users across different decision-making environments. Hannula and Pirttimaki (2003), in their survey-based study, found the most significant benefits, provided by BI&A, were the acquirement of better quality information for decision making, improvement in the ability to anticipate threats and opportunities as well as the growth of knowledge base and time savings. Despite the importance of these studies in the identification of factors influencing delivered value through improved decision-support, it remains unclear how new knowledge is obtained as a result.

Other studies research the type and measurement of value that is generated from BI&A use. Hence, Watson (2009) and Watson and Wixom (2007) found BI&A to generate a range of benefits from local impacts (such as, cost savings from data consolidation, time savings from the user), to global ones, such as, more and better information, better decisions, improvement of business processes, which are ultimately difficult to assess due to their "soft" nature. In addition, Clark, Jones, and Armstrong, (2007) have presented a theoretical model of benefits from BI&A and other decisional support technologies and have found value to be difficult to measure, since many organizational factors such as culture, the use of information, management commitment can heavily influence the BI&A perceived value and are also difficult to assess. Nonetheless, Davenport and Harris (2007), in a multiple case study research, found BI&A resources to be an insufficient source of value if not coupled with sufficient data analytical capability and a strong analytical culture. Even though they discussed the potential benefits from BI&A use in a more detailed or cursory fashion, one gets the impression that technology delivers value in some inert form that can be transferred and controlled.

Until now, researchers have examined the BI&A value creation process using a variety of theories and empirical approaches. Since most of the studies of IT value creation ground their studies on a Resource-Based Theory (RBT), Dynamic Capabilities Perspective, and Information Processing View (Bharadwaj, 2000; Melville, Kraemer, & Gurbaxani, 2004; Ryu & Lee, 2013; Santhanam & Hartono, 2003; Trkman et al., 2010; Wang & Ahmed, 2007), recent studies of BI&A value creation have used similar theoretical foundations (Cao, Duan, & Li, 2015; Cao, Duan, & Cadden, 2019; Côrte-Real, Oliveira, & Ruivo, 2017; Fan et al., 2015; Fink et al., 2017; Kowalczyk & Buxmann, 2014). In accordance to Trieu (2017) call for consideration of firm factors (such as organizational size, scope, and absorptive capacity) while investigating the relationship between BI&A assets and impact on understanding the dependence of its value on organizational resources allocation, we reviewed the theoretical foundation of the Absorptive Capacity Theory and the BI&A assets to identify conceptual ideas as a guideline in preparing interviews.

2.3. Theoretical foundation

2.3.1. Absorptive capacity

In their research on innovation, Cohen and Levinthal (1990), p. 128) conceptualized a firm's absorptive capacity as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends." It depends on the prior related knowledge which allows firms to better evaluate the signals for technological advances and development. Absorptive capacity, therefore, allows identification of new knowledge by an organization from outside the organization and the assimilation and integration of knowledge within existing knowledge internally (Arora & Gambardella, 1994; Cohen & Levinthal, 1990; Kogut & Zander, 1992). Thus, there is not only new knowledge generation but also competence leverage is required to exploit existing technologies (Danneels, 2002). This classifies absorptive capacity as integral to dynamic capabilities since it allows for continuous acquisition, search, and management of knowledge (Pavlou & El Sawy, 2010). An absorptive capacity enhances the interaction of the organization with the external environment through greater external knowledge assimilation as well as improving knowledge sharing and learning between organizational subunits (Rosenkopf & Nerkar, 2001).

It is important for the firm, however, to constantly invest in the development of its absorptive capacity, since the firm might become not be aware of the technological opportunities and signals in a given field (Cohen & Levinthal, 1990; Kogut & Zander, 1992). Thus, organizations with high levels of absorptive capacity are proactively exploiting technologies and market opportunities in the environment independent of their current performance by combining both internal and external knowledge sources. Organizations with a modest level of absorptive capacity are more reactive, responding to some performance criterion (Cohen & Levinthal, 1990; Lavie & Rosenkopf, 2006; Rothaermel & Alexandre, 2009). The higher the level of absorptive capacity, the higher the spillovers between internal and external knowledge sourcing (Rothaermel & Alexandre, 2009).

Roberts, Galluch, Dinger, and Grover, (2012) emphasized a few important assumptions underlying the absorptive capacity. Firstly, absorptive capacity is domain-specific. The ability to determine the value of the external knowledge depends on prior-related knowledge. Although it is important that the firm's existing knowledge overlap with external knowledge for successful acquisition, a strong overlap will limit new opportunities and insight generation (Lord & Ranft, 2000). Secondly, absorptive capacity is firm-specific. Absorptive capacity depends on the absorptive capacities of a firm's individuals; however, it is not just the sum of the individuals' capacities, but is also composed of the overlapping of individuals' knowledge and the knowledge transfer across and within subunits (Cohen & Levinthal, 1990; Roberts et al., 2012). Effective information and knowledge obtainment require both structures and processes that increase the quality and quantity of information and knowledge and can integrate it into collective action (Sheremata, 2000, p. 405). As individuals from various departments obtain and interpret knowledge in various ways, internal communication and integration are important for improving the quality of learning (Brown & Eisenhardt, 1995; Nonaka, 2007). The increased information flow can cross-functionally enhance the quality of learning. Thirdly, absorptive capacity is path-dependent. Absorptive capacity accumulation in one period will, therefore, allow more efficient absorptive capacity accumulation into the next. For effective organizational learning, there must be a balance between inward and outward-looking absorptive capacity, since excessive dominance by one of them is dysfunctional (Cohen & Levinthal, 1990; Grant, 1996). If the body of expertise becomes sufficiently specialized, it could impede the assimilation of external knowledge, resulting in the so-called Not-Invented-Here Syndrome, in which firms reject innovative ideas from the environment (Cohen & Levinthal, 1990). Lack of external knowledge openness and past experiences lacking in reward may reflect organizational myopia towards different external sources (Levinthal & March, 1993). Path-dependency allows firms to predict more accurately the potential of technological advances.

As Grant (1991) discussed, assets are the basic unit of analysis, whereas capabilities are integrated arrangements of assets. Hence, as Fink et al. (2017) and Lin and Wu (2014) argued capabilities represent the primary source of the value and are often seen as a converter of organizational resources/assets into a competitive advantage. Several conceptualizations of the construct of absorptive capacity can be found in the literature (Jansen et al., 2005; Todorova & Durisin, 2007; Zahra & George, 2002). In line with prior research, we define absorptive capacity as a second-order dynamic capability that builds, integrates, and reconfigures underlying first-order capabilities and zero-order assets to create and deploy knowledge (Gao, Yeoh, Wong, & Scheepers, 2017; Wang & Ahmed, 2007; Zahra & George, 2002). Hence, absorptive capacity is captured by four first-order capabilities that reflect dynamic processes, such as acquisition, assimilation (potential absorptive capacity), transformation, and exploitation (realized absorptive capacity) (Flatten, Engelen, Zahra, & Brettel, 2011; Lane, Koka, & Pathak, 2006). The first capability – acquisition, refers to the identification and obtainment of information through external sources relevant to the firm's operations and is affected, as well, by the prior knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). The second on - assimilation, refers to the firm's ability to analyze, interpret and understand externally acquired information (Cohen & Levinthal, 1990; Flatten et al., 2011). The third capability - transformation, refers to developing routines that facilitate a combination of existing knowledge with new, acquired knowledge and internalization of this knowledge (Zahra & George, 2002). The last one – exploitation, refers to an application of the acquired, transformed knowledge to commercial ends (Cohen & Levinthal, 1990). The four first-order capabilities of absorptive capacity together enable firms to exploit new knowledge, enhance the firm's performance and achieve competitive advantage through new product innovation. However, absorptive capacity not merely connects the first-order capabilities but combine them creating synergistic outcomes (Lichtenthaler, 2009; Raisch & Birkinshaw, 2008; Wang & Ahmed, 2007). Nevertheless, following recent Gao et al's (2017) recommendations, we examined absorptive capacity on an organizational level of analysis in the behavioral domain of study, which refers to activities and application of the technical domain.

2.3.2. Underlying BI&A assets

As the process of knowledge extraction does not happen in isolation, different BI&A resources either facilitate or inhibit knowledge accumulation and utilization. Thus, the BI&A business value has been found to be contingent on the underlying BI&A resources/assets (Fink et al., 2017; Wieneke & Lehrer, 2016). Extant literature has already presented some potential resources/assets that could impact the value creation process. For instance, Cosic, Shanks, and Maynard, (2015) presented four categories of organizational resources and capabilities, such as governance, culture, people, and technology capabilities. Further, Shuradze and Wagner (2016) proposed three groups of assets for data analytics, such as technological infrastructure, personal expertise, and relational infrastructure. Similarly, Wieneke and Lehrer (2016) presented physical, human, and organizational resources as a basis for social-media insight exploitation. Nevertheless, Castro, Delgado-Verde, Amores-Salvadó, and Navas-López, (2013) described human, technological, and relational assets for intellectual capital creation and product innovation. Based on the reviewed literature, we identified technological, human, and relationship assets that may underpin the first- and second-order dynamic capabilities of absorptive capacity, influencing the knowledge creation process in the BI&A context. Thus, we consider assets as raw material that would affect the capabilities' development process (Ravichandran & Lertwongsatien, 2005; Wade & Hulland, 2004).

Here, technological assets refer to technical platforms, IT infrastructure, physical IT assets, data repositories, communication technologies, and IT architectures (Bharadwaj, 2000; Wade & Hulland, 2004). Technological assets, such as databases and networks are easily acquired in the market, in contrast to sophisticated IT infrastructure and communication technologies which are difficult to imitate. IT technological assets have found to enhance a firm's absorptive capacity (Roberts et al., 2012; Yeoh & Popovič, 2016). Technology allows firms to codify, process, store and recover information that has been acquired (Argote, McEvily, & Reagans, 2003). Next, it facilitates knowledge diffusion across different business units or networks for further transformation and exploitation (Lee & Choi, 2003). In summary, it enables firms to acquire, process, manage and share data and information for meaningful insights generation and, furthermore, allows fast and cost-effective integration of new technologies with existing ones (Ravichandran & Lertwongsatien, 2005).

On the other hand, human assets refer to workforce business knowledge, technical skills, work experience and relationships (Barney, 1991; Teece, 1998). Prior research has shown the importance of human assets for absorptive capacity capability. Namely, employees with strong business knowledge and technical skills are more efficient in recognizing and valuing new external knowledge, therefore, increasing the knowledge level in the firm (Lund Vinding, 2006; Mangematin & Nesta, 1999). Moreover, greater work experience increases the accumulation of firm-specific knowledge, increasing the ability to transform and exploit assimilated knowledge (Zahra & George, 2002).

Nonetheless, relationship assets encompass inter-divisional relationships, external (client) networks, management sponsorship and culture (Ross, Beath, & Goodhue, 1996; Wade & Hulland, 2004). The knowledge transfer across different business units enable intra-organizational knowledge flows and knowledge consolidation (Cohen & Levinthal, 1990), which in turn, increases both the recipient's knowledge base and organization's knowledge base (Pawlowski & Robey, 2004). Organizational culture strongly influences these processes (Verona & Ravasi, 2003).

3. Research context and the methodology

3.1. Sample and procedures

The main objective of the exploratory inquiry was to examine how BI&A triggered insights are transformed into valuable knowledge and what the underlying capabilities and assets are. We found the exploratory methodology of the research suitable since the phenomenon is new, broad and complex, so it is difficult to identify causal relationships (Corbin & Strauss, 1990; Eisenhardt, 1989; Pare, 2004). The exploratory analysis aids to extend existing theory, offering additional insights into the complex relationship between the constructs (Denzin & Lincoln, 2005; Eisenhardt & Graebner, 2007). We apply abductive scientific reasoning (Mantere & Ketokivi, 2013; Strauss & Corbin, 1998), where initial inductive insights from empirical data are engaged with existing theoretical knowledge to explain the empirical puzzle then. We assume the semi-structured interview to be the most effective method of gathering information for our research since it is flexible and accessible enough (Alvesson, 2003; Brinkmann, 2014; Holstein & Gubrium, 1995).

We followed the theoretical, purposeful sampling approach in selecting participants in the study to ensure a relevant representation of the actual state (Denzin & Lincoln, 2005). Nine European firms from different sectors: high-tech, manufacturing, telecommunicative, service-oriented, retail, financial, and energy were selected to conduct the interviews. Acknowledging the fact that larger firms are more able to invest in different IT technologies with related employee training (Chatterjee, Grewal, & Sambamurthy, 2002; Elbashir et al., 2013), we have, therefore, considered medium and large-sized firms. The expert interviewees had to fulfil l the following screening criteria: (1) having deep knowledge about the organization; (2) having more than three years of experience in BI&A initiatives, and (3) being at leading IT or management position. According to the needs of this study, we selected fourteen expert interviewees/key informants, in positions within the variety of Chief Executive Officer, Chief Information Officer, IT manager, Head of R&D, or Market Research Manager. Out of fourteen, five key informants were selected through the snowballing method. All of them possessed and actively used BI&A in their everyday work. Thus, over a two-year period (between February 2016 and October 2018), we carried fourteen interviews involving nine firms. Table 1 provides a breakdown of the informants included. The relatively small sample size of interviews was, however, sufficient to generate theoretical saturation, whereas, the new interviews provided no additional data that lead to any new emergent themes, as discussed by many authors (Boyce & Neale, 2006; Crouch & McKenzie, 2006; Urquhart & Fernandez, 2016). Moreover, increasing the sample size may question the ability of the researchers to devote sufficient attention to dataset analysis (Marshall, Cardon, Poddar, & Fontenot, 2013). All the firms, included in the research, had used BI&A for several years at that time and were appropriate candidates to illuminate the BI&A value generation process when the study was conducted.

With each interviewee, we conducted a semi-structured interview

Table 1
Informants data.

Firm	Number of informants/ Position	Country	Industry sector	Mode
A	1: CEO	Croatia	Services	On-site
B	1: Chief Information Officer	Slovenia	Software	On-site
C	2: CEO; IT manager	Austria	High-tech industry	Skype
D	1: Market Research Manager	Germany	Software, IoT	On-site
E	2: IT Manager, Head of R&D	Germany	Manufacturing	Skype
F	2: IT manager, Managing Director	Germany	Telecommunications	Skype
G	1: Chief Information Officer	Slovenia	Retail	On-site
H	2: IT manager, Managing Director	Slovenia	Financial	On-site
I	2: IT Manager, Head of R&D	Slovenia	Energy	On-site

based on the interview protocol (Appendix), with an average duration of one hour. We asked all informants participating in the study to speak as the representative voice of the collective. Firstly, we collected data about interviewees' position as well as experience and general data about the firm. Next, after presenting the goal of the research, we asked the interviewees to describe their understanding of BI&A, discussing the highlighted topic and the use of it in as much detail as possible. Since the specific purpose of the interview was to learn as much as possible about the interviewees' perceptions and concerns about BI&A, we asked a set of open-ended questions. At the end of the interview, each participant was asked for other details that might be relevant to the interview. Since some of the interviewees did not allow tape-recording, we took detailed field notes during the interviews, complementing them with detailed notes immediately after they were completed. Although we acknowledge that taping would provide richer and more accurate data, we had to consider the participants' requirements. After each interview, a systematic analysis of the notes taken was completed.

3.2. Data analysis

The data analysis procedure followed the guidelines specified for methods of naturalistic inquiry and constant comparison (Charmaz, 2006; Glasser & Strauss, 1967; Schwandt, Lincoln, & Guba, 2007). The latter allowed us to adjust iteratively theoretical categories and delineate aggregated dimensions. Each interview was systematically examined and systematized within the categories. To assure better quality and accuracy of the coding process two independent reviewers coded the same data. We started with identifying initial, first order codes that were informant-centric (Corbin & Strauss, 1990). Next, we used axial coding, seeking similarities and differences between and amongst these categories, assembling first-order codes into theoretical categories. Finally, after coding saturation regarding the refining categories that had been reached, we distill the emergent theoretical categories into aggregate theoretical dimensions. We have, however, finished these steps in a recursive analytic procedure (Locke, 2002). At the end of the coding process, we calculated the interrater reliability among the two coders, and we reached a high level of agreement (0.92), considering to be a justifiable verification of the coding procedure. The final data structured is summarized in Fig. 1 and details have been described in Section 4. To assure better quality and accuracy of the coding process, we used peer debriefing (Creswell & Miller, 2000; Schwandt et al., 2007; Spall, 1998). We have, hence, invited two external peers (departmental members), that were not included in the research to evaluate and reflect on the data collection and analysis procedures. A detailed search for disconfirming evidence was conducted until we reached a strong level of agreement.

4. Findings

This section presents our findings, drawn on the interview data. The origin of data, presented in the quotation marks below, is extracted from the field quotes and the observation field notes, verbatim.

4.1. BI&A definition and characteristics

We asked interviewees to describe how they define BI&A and what is the importance of that technology for their firm. Before offering a concrete definition, different interviewees highlighted different properties depending on the degree of BI&A use. As Interviewee 3 noted: *"In general, business intelligence and analytics means an advanced analysis to generate intelligence from business data for improving business. We apply advanced techniques, like data mining, semantic and network analysis, and machine learning to understand our customer preferences, mostly real-time. This allows us to articulate the problem, which is something that was difficult with transactional data and conventional analytics"*. Similarly, Interviewee 7 said: *"It is the advancement of BI technology and techniques that fit into new developments and gather timely information. Without real-time or close to real-time market information, we lag immediately behind the competition"*. Moreover, Interviewee 12 noted, "*It is a bunch of technologies, that allows us to create a real-time relevant knowledge, based on prior and current customer information."* Interviewee 14 elaborated "*BI&A are technologies and methodologies that help our firm predict future trends to enhance the reliability of the decision-taken. Hence, we mainly rely on predictive analytics, machine learning, and regression for better pattern recognition*". On the other hand, some interviewees did not agree with the strict distinction between traditional BI and BI&A. Thus, Interviewee 1 commented: *"It is nothing, but traditional database business intelligence suited for larger datasets that are used for knowledge discovery. Currently, some fads appear to be new, revolutionary but are only an evolution of existing technologies and techniques"*.

However, most of the interviewees highlighted the so-called "big data" challenge; regarding increased volume, variety, and velocity of data generation. Thus, Interviewee 2 noted: *"The main difference between the older BI and BI&A is in the challenge to analyze and store large, unstructured and complex datasets, presently known as big data, requiring unique technologies. Here, we try to develop new approaches to make sense of the massive amount of data we collect as well as generating previously unknown insights. All of which is, however, easier said than done"*.

Nonetheless, they emphasized the importance of the value of information as a crucial component in obtaining competitive advantage: *"We found the main difference between traditional BI and business analytics to be in the specific approaches made to realize the value in understanding the customer, competition, and market behavior. We collect an enormous amount of data from smartphones, social media, and the Internet. It is, however, not about how much you have, but what you have in your hand when deciding. It requires us to develop different abilities. Otherwise, we could quickly become obsolete."* (Interviewee 9). Thus, most of them agreed that new, valuable insights are the greatest benefit from BI&A use.

4.2. Underlying capabilities: absorptive capacity perspective

The interviewees recognized the role of BI&A processes for insight and knowledge generation. To incorporate BI&A's generated insights into the value creation processes, we draw on four distinct, but complementary absorptive capacity capabilities: acquisition, assimilation, transformation, and exploitation, as suggested by Carlsson (2003) and Zahra and George (2002). Thus, we used the absorptive capacity's theoretical lens as a sensing device to analyze empirical data. However, all the claims are grounded in empirical, field data.

The analysis of the interviews emphasized the role of strong acquisition capability for being able to identify and obtain valuable data from external sources. Namely, the overwhelming amount of data from external sources requires careful cleaning, conditioning, and integration of data sets to make them usable. This is a demanding process since data is often the origin in heterogeneous sources, coming with noise,

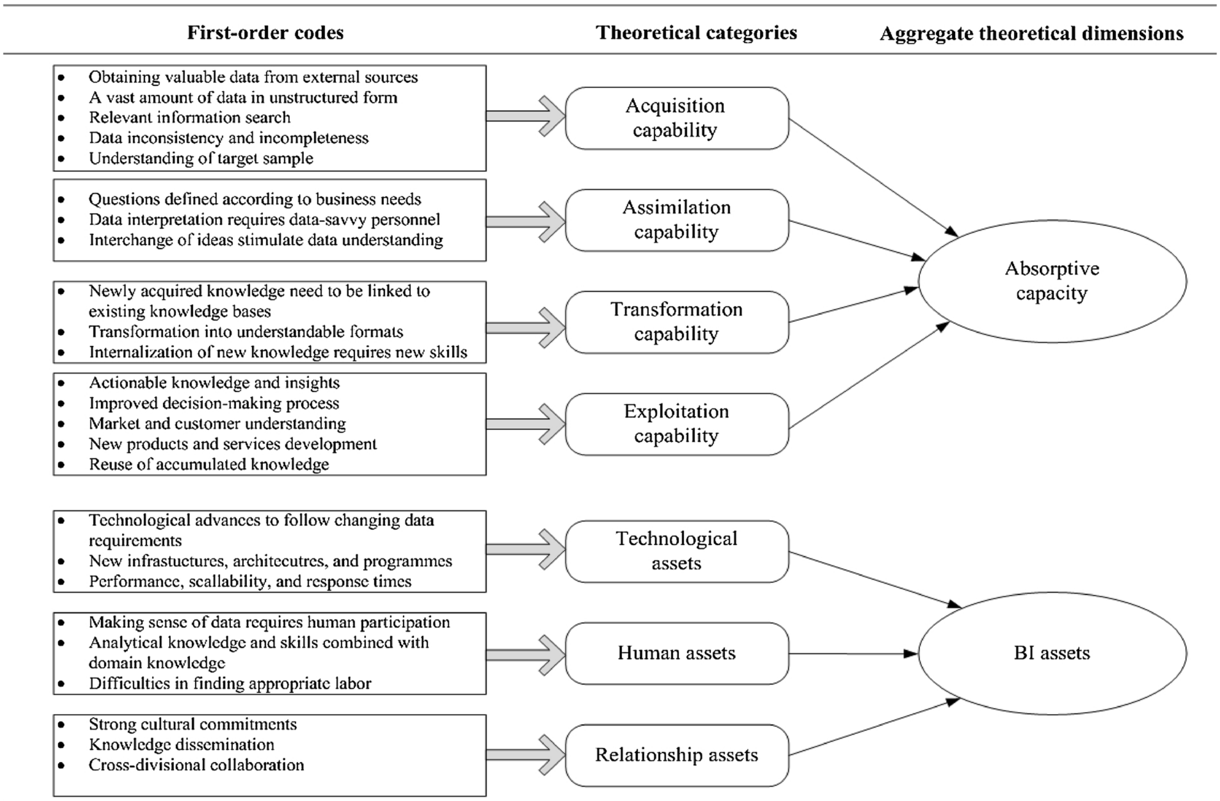

Fig. 1. Overview of the data structure.

opacity, and incompetencies (Gandomi & Haider, 2015). The increased volume and unstructuredness of data has increased storage costs, adding real-cost to firms. Thus, it is crucial to have the ability to determine the value of retaining data for future actions, as noted by Interviewee 4: *"Although data can be a source of useful insights, we have quite often a problem with data inconsistency and incompleteness. We spend hours and hours cleaning data, deciding which attributes to keep, how to represent and analyze them, which, however, often results in wasted time and money"*. Moreover, firms reported an increased collection of information from social networks as a source of data (such as Facebook, Twitter, LinkedIn), has shown, many times, to have a limited scope as well as limited quality. Instead of assuming social networks are representing the whole population, firms should assume users as a sample, requiring critical examination and understanding of the target sample. As Interviewee 6 noted: *"We made a huge mistake by collecting all datasets related to our business problem. This lead to storage problems, endless search, and inconsistent insights. Unfortunately, it cost us a fortune to figure out that we needed to target collect data"*.

Additionally, the interviewees highlighted the importance of a firm's assimilation capability in processing internal and external data. To be able to capitalize on the generated knowledge, firms must define the business needs and objectives, while defining the right questions. As mentioned by Interviewee 2: *"Our IT professionals require specific questions to be asked upfront that would clean and prepare samples out of the whole dataset. When we don't know what to ask or don't understand the sample, the abundance of noise in datasets lead to weird conclusions."* Hence, Interviewee 13 commented "*We use challenging as a technique for asking a relevant research question. The one that orders particular analysis must come with a clear estimate about what is the potential added value of the analysis, and what are the potential outcomes"*. Therefore, human intervention is crucial in making sense of data. Interpretation of externally acquired information requires data savvy decision-makers who can estimate and understand the potential insights' value. Since developing IT skills for management personnel can be a time-consuming process, the interviewees suggested a close collaboration between IT and managers. For instance, Interviewee 5 commented: *"We ask our managers to work closely with IT personnel to tackle the challenge of data interpretation, which offers us a strong basis of heterogeneous expertise in IT, marketing, and customer relationships."* Similarly, interviewee 10 noted: "*Our data scientists work together with the reporting staff to create useful recommendations for the decision-makers*." Nevertheless, Interviewee 13 remarked: "*We believe we are much stronger when complementing our knowledge and capabilities. Hence, we don't want a single person that is knowing everything. Instead, we create teams, that complement each other's knowledge. Otherwise, you will reach an adverse effect, having people that are mediocre in everything"*.

Transformation capability was found to play an important role in facilitating the internalization of newly, acquired knowledge within an existing knowledge basis. Having amazing insights does not mean one has succeeded. These insights need first to relate to an existing knowledge base and then to be disseminated within the organization to reach persons that need them for decision-making or an action-taking improvement. However, interviewees emphasized the importance of an insight's format that is clearly and easily understood: *"We ask our teams to transform results in graphics, dashboards, and interactive visualizations so that other less data-savvy personnel can access and comprehend their value in a more intuitive manner"* (Interviewee 3). Similarly, Interviewee 11 elaborated: *"We are increasingly relying on data visualization to present the mined information in a comprehensible manner*." In contrary, an employee's resistance to BI&A, as a response to information overload, appeared to impede the internalization of new knowledge. Following that, Interviewee 6 noted: *"We were forced to organize different educational courses and workshops to develop skills of information assessment and interpretation."* Nevertheless, employees became more confident in BI&A use after equipped with the appropriate skills and knowledge.

Finally, the exploitation capability has been found to allow transformed knowledge commercialization. Our interviewees reported BI&A insight use for a different purpose: to understand customer and market behavior, optimize business processes (decision-making, supply-chain), optimize advertisement campaigns and pricing strategies, develop new products and services, manage financial risks, improve efficiency, identify faults and to provide proactive machine maintenance. However, as noted by Interviewee 8: *"It requires a lot of effort to maximize the value of generated insights. We motivate our employees to search our databases for generated knowledge, continuously, to support their everyday decisions"*. Thus, applying reuse as well as the formation of already generated knowledge can increase BI&A insights value, which in turn could enhance firm performance.

4.3. Underpinning assets

We identified technological, human and relationship assets to form the basis for absorptive capacity capabilities. In the following subsections, we elaborate on each in detail.

4.3.1. Technological assets

Most of the interviewees highlighted the importance of advancement in technology to maintain changing data requirements. Thus, a major shift from transactional to behavioral data pushes firms to upgrade their technological assets, regarding infrastructures, architectures, and programs. Interviewees reported using different BI&A assets, such as data and text mining, regression, OLAP, search engines, multivariate analysis, process, and network mining, cloud computing, parallel programming, opinion mining, sentiment analysis, visualization, social media analysis, and natural language processing. Accordingly, Interviewee 2 discussed the following: *"We were forced to go beyond traditional, relational databases to fit the requirements of new, unstructured, massive datasets. Thus, we adopted the MapReduce parallel computing tool and Hadoop database technology, which allows us to integrate new, external data with internal data."* Despite the excitement about the possibilities of advanced programs, infrastructures, and architecture offer, most of the interviewees complained about drawbacks, like poor performance, scalability and long response times. Moreover, the needed learning processes needed to achieve skillfulness are both time and finance-consuming. Hence, Interviewee 10 remarked: *"One of the greatest obstacle related with advancing usage of BI&A is the time constraint. The employees are already overloaded. Thus, successful usage of the BI&A solution requires additional financial investments"*.

Nonetheless, interviewees pointed out the role of BI&A assets in facilitating internalization of acquired knowledge. With the increasing storage costs, however, firms decreased their appetites towards valueless data retaining. Only valuable knowledge is saved in joint repositories, which make it available for future knowledge discovery. Thus, the technological advancement offered powerful visualization techniques for knowledge discovery. As one IT manager noted: *"Our managers often have difficulties in understanding complex data. For that reason, we try to present results in the form of interactive visualizations or graphs, and then, together, analyze details and potential applications"* (Interviewee 6). Similarly, Interviewee 12 commented, "*We can hardly force continuous usage of the generated information if not presented in a synthe sized way in the form of easy-understandable graphs and visualization, complemented with recommendations and specifications, where could be this information relevantly used."* Although there is a noticeable advance in the visualization approach, they still have been found by our informants to be scarce and time-demanding.

4.3.2. Human assets

Although much of the current enthusiasm refers to technological assets, human assets have begun to be emphasized as a critical milestone in succeeding with BI&A. While not neglecting important technological breakthroughs, informants have stressed the role of the human factor in making sense and use of data and insights. Ideally, these firms need multidisciplinary data scientists that own a combination of data, analytics and business knowledge which would allow them to communicate with, and understand, the broader business environment. However, most of the IT that professional firms have employed are trained in Computer Sciences, Statistics, and Mathematics, lacking overall business knowledge and struggling to interpret data for a firm's performance enhancement. According to Interviewee 4: *"It is extremely hard to find a suitable workforce that has considerable expertise in both analytics and business issues. Usually, they come with strong data and a computational focus."* Moreover, as Interviewee 13 commented "*We don't even look for data scientists that have advanced business knowledge. Although they are welcomed, we are at the first place looking for IT professionals, that can use a "common sense" and are good team players. Then, we create teams consisted of different professionals to work together on a particular project"*. Therefore, firms have reported recruiting professionals with strong technical and analytical skills to model, analyze and manipulate data; then, organizing them into teams with business managers, where IT expertise is combined with deep domain knowledge for collaborative data exploration.

Additionally, interviews reported that data analysis shortage seriously constrains the possibility of insight generation. As is exemplified by Interviewee 7: *"We can find IT professionals, however, not all of them are equipped with the needed technical, data and analytical skills necessary to exploit the technology fully. Thereby, we started a collaboration with universities to develop an educational curriculum that would address this labor issue."* Still, recruiting technically and analytically sound data scientists remains to be a large challenge.

4.3.3. Relationship assets

Although they had been using BI&A for some time, interviewees mentioned some organizational factors that notably influence successful use. Firstly, it was mostly agreed upon that strong decision-making culture could significantly impact on creating a competitive advantage with analytics: *"Our higher-level management is often reluctant to use BI&A to support their actions and decisions. Some of them still believe their experience and intuition are the most secure source of knowledge when deriving strategic decisions. Unfortunately, this impacts on lower level management, leading them to be skeptical about the advantages of utilizing this technology"* (Interviewee 4). Similarly, Interviewee 11 remarked *"We still rely to a great extent on intuition. It is difficult to convince the decision-makers that mixing both is beneficial"*. Hence, Interviewee 12 added "*I suppose I should not talk like this, regarding the fact I am a data scientist, but we believe data triggered insights just complement intuition. Prior related knowledge and experience are very important in making the correct decision."*

Unsurprisingly, many interviewees emphasized the effort it takes to build strong, cultural commitments while incorporating BI&A into day-to-day activities. As Interviewee 7 noted: *"We started using BI&A without considering the level of commitment it requires to be successful. Culture became a greater obstacle than the technology itself. It was a long process to make the technology trustworthy to our employees."* Hence, as Interviewee 13 commented *"Cultural commitments could be built only if you prove your employees that data provide added value"*.

Many firms prompted their employees to collaborate cross-divisionally, to compensate a potential lack of skills and capabilities. Moreover, reliable, information-centralized knowledge bases have been found important; since it allows further knowledge dissemination, transformation and exploitation, especially when data-mindset is a prevalent cultural pattern. This, however, requires aligning an existing, overall firm strategy with the contemplated data strategy.

5. Discussion

The increasing prevalence of BI&A research impacted scholarly attention to understanding the mechanism trough witch BI&A use creates value. We add to this line of inquiry by examining the issue of how BI&A triggered insights are transformed into valuable knowledge. The extant literature on the BI&A value creation highlights the process mostly regarding improved decision-making that could drive business performance (Chen et al., 2015; Fan et al., 2015; Sharma et al., 2014; Wieder & Ossimitz, 2015). Here, scholars have relied on the presumption that BI&A uncover useful information that is used by decision-makers across different business levels to make better, and more informed decisions. Rather than viewing the technology as a 'passive container,' which produces knowledge that is ultimately used in a decision-making process, our analysis exhibits the absorptive capacity to underlie the process of raw data transformation into valuable knowledge for action-taking and decision-making. Instead of positioning BI&A exclusively as a decision-supporting tool, our analysis underlines that firms should develop higher-order dynamic capabilities to allow continuous acquisition, search, and management of knowledge. This is in-line with some recent works (Fink et al., 2017; Shollo & Galliers, 2016) that warn a limited understanding of the concept when overlooking the role of BI&A in organizational knowing, but extending by showing how different BI&A resources and lower-order knowledge capabilities are integrated and reconfigured by the higher-order dynamic capability of absorptive capacity for knowledge creation.

5.1. Theoretical contributions

This study offers several theoretical contributions to the understanding of the BI&A value creation process. Our study suggests that might be insufficient to focus on the improved-decision making, without considering how knowledge creation occurred in the first place. We contribute to this research vein by focusing specifically on the mechanism trough witch different knowledge creation capabilities interplay with organizational resources to create useful organizational knowledge. Thus, this article offers few implications for research on business intelligence, knowledge management, and dynamic capabilities. First, it integrates prior research on BI&A use and absorptive capacity by specifying the underlying, first-order capabilities of absorptive capacity in the context of BI&A. Beyond that, our paper emphasizes the importance of the underpinning technological, human, and relational assets, while specifying the role of absorptive capacity as a second-order dynamic capability that builds, integrates, and reconfigures the underlying capabilities of acquisition, assimilation, transformation, and exploitation and the underpinning assets. As such, this study echoes the call by Gao et al. (2017) to establish the importance of the absorptive capacity in the BI&A domain, while considering the call by Trieu (2017) for considering a firm's factors when investigating the relationship between BI&A assets and BI&A impacts. With this integrated perspective, scholars might have better awareness of the BI&A value creation process.

Although technological appropriateness of the BI&A has been widely argued to be an essential catalyst of the successful BI&A use (Chaudhuri et al., 2011; Chen et al., 2012; Watson & Wixom, 2007), the importance of human assets that underpin the knowledge creation processes has only recently started to be investigated (McAfee et al., 2012; Ransbotham, Kiron, & Prentice, 2016). Our research extends this stream of thinking by identifying human assets as crucial for successfully delivering value from BI&A use. Namely, our informants emphasized the importance of having personnel equipped with both, domain and data knowledge, so pattern identification and insight discovery are possible. Since the value of the information, contained in some data, depends mainly on the intended application and the contextualization (Popovič, Hackney, Tassabehji, & Castelli, 2016), firms must set in place strong human assets, equipped with domain-specific knowledge (Wixom, Yen, & Relich, 2013) that are able to ask relevant business question. Considering the importance of technological assets, the empirical findings have emphasized the role of human assets in making sense and use of data, since the technology itself is outpacing the ability of the firm to deploy technology effectively. In line with some recent research (Davenport & Patil, 2012) we found important for firms to allow close collaboration of IT and management personnel to cope with the shortage of skills successfully. Moreover, since learning is a cumulative process (Cohen & Levinthal, 1990), richness and relevance of prior, related knowledge will allow better knowledge assimilation. The interpretation of externally acquired information is possible when the "modern" gatekeepers are equipped with multidisciplinary knowledge and skills; which allows them to estimate and understand information for a potential benefit (Altman, Nagle, & Tushman, 2014; Staggers & Nelson, 2015).

We complement this research inquiry by showing how technological and relational assets underpin the first-order capabilities of knowledge creation, something that prior research has considered in isolation. Consistent with some prior research, our findings suggest that the inadequate, complex presentation of the BI&A triggered insights might jeopardize the use of information (McAfee et al., 2012). Hence, the technological assets should allow a presentation of newly generated knowledge in formats that are more palatable (graphics, dashboards, visualizations), so that it can be easily comprehended and accessed by less data skilled personnel. Thus, the study turns attention to the potential drawbacks of BI&A use, regarding poor, technological performance, scalability, long response times, high storage costs, labor shortage, and long learning processes, which ultimately lead to reluctance in BI&A use.

Nonetheless, our findings indicate that the commercialization of transformed knowledge through the exploitation capability requires continuous search and reuse of generated knowledge, which further allows improvement of different business processes, improvements of the development of products and services, the understanding of customer and market behavior and managing risks, etc. We have found that the relationship assets significantly influence the realized absorptive capacity capabilities (transformation, exploitation). Moreover, our findings revealed skepticism about the advantages of BI&A amongst higher management levels, leading to some hesitation to incorporate BI&A triggered insights into decision-making or action-taking processes. Therefore, companies need to invest in cultural changes to achieve a decision-making culture which blends the analytics' insight with a managers' intuition that would produce better, effective results than each could individually. Although previous research has also discussed how overturning intuition and consequential management could limit the potential value of BI&A for firms (Bronzo et al., 2013; Fallik, 2014; Ransbotham et al., 2016; Trelles, Prins, Snir, & Jansen, 2011), we extend this research vein by assessing the impact on the first-order knowledge capabilities of absorptive capacity. Therefore, this study highlights the need for aligning existing firm with the considered data strategy, while developing a strong data culture, tolerable for mistakes.

5.2. Implications for practice

In addition to theoretical contributions, this study suggests several important implications for practicing managers. First and foremost, our study emphasized the crucial role of absorptive capacity in building, integrating, and reconfiguring assets and first-order knowledge capabilities for knowledge creation from BI&A. Our findings pointed out that the value of the information in the first place comes from the intended application. Hence, firms should avoid irrelevant business questions, which are possible only if sufficient domain-specific knowledge and IT expertise are set in place. Organizations should provide systematic training and education to develop data-savvy personnel or create teams of data scientists and business professionals that could together translate the results of a complex model into simple information to digest.

Extending this discourse, we highlighted the importance necessary to align existing firm culture with the required capabilities. Our findings suggest that a firm needs strong cultural commitments and symbiotic data and strategies to eliminate organizational barriers for delivering BI&A value. A continuous dialogue between human intuition and analytic statistics will allow better decision-making, based on real-time evidence. However, along with the openness to new ideas from data analytics, tolerance for mistakes must be present, since people cannot know which results would work out (Ransbotham et al., 2016). Failure to align the required capabilities, assets and culture could lead to defective decision-making (Erevelles, Fukawa, & Swayne, 2016; Jaklič, Grublješič, & Popovič, 2018; Matzler, Bailom, & Mooradian, 2007). Thus, all management levels must be aware of the ability of BI&A to provide more holistic and accurate market intelligence, which requires continuous organizational effort.

Nevertheless, our study suggests that consistent BI&A use in day-to-day activities, as well as decisions, are only possible if the technology is trustworthy. Firms need to upgrade existing BI&A infrastructures, architectures, and software to fit the data changing requirements. Our findings emphasized the importance of a presentation of information in forms of interactive visualizations and graphs, which further reduce the effort it takes to interpret and manage new insights. However, poor performance, scalability, long response times, and high-costs could be an important obstacle that leads to potential BI&A underuse, limiting the potential in BI&A value.

5.3. Limitations and outlook

A few limitations of this study are worth noting. First, the empirical data was collected from a sample of nine medium and large-sized firms from European countries. Although we believe that the analysis has provided insights that are valuable in context with small-sized firms, we cannot make claims that small businesses, within the often-limited market of technological knowledge, could benefit from BI&A at the same level as larger firms. Moreover, since we have selected European firms only, we could not observe how the BI&A value creation process would vary across different cultural contexts. Our focus on these selected firms, from eight high-knowledge, intensive sectors used to conduct the analysis, could also be seen as a limitation. An in-depth analysis across other, less knowledge-intensive industries may reveal additional insights. Accordingly, we encourage future studies to investigate the similarities and differences in context with this study regarding a firm's size, cultural context, and industry. Next, future research could test the theory and draw causal inferences in quantitative research design to complement the findings we have outlined here. Finally, even though we have carefully and thoroughly studied and taken notes, we are aware that notes taken do not provide a complete verbal record (Muswazi & Nhamo, 2013). Therefore, the note-taking made may have affected the accuracy to reconstruct what the interviewees have said.

5.4. Conclusion

BI&A has been often promoted to deliver competitive value gains. The findings of the present study shed light on how knowledge is created from BI&A triggered insights. Applying the absorptive capacity's theoretical lens, we explain the interplay of the absorptive capacity's underlying capabilities with the underpinning assets, providing a theoretical explanation of the process of delivering value regarding knowledge creation. Hence, we establish the importance of absorptive capacity in the BI&A domain while considering the impact of BI&A assets, providing an important basis for future research on the BI&A value creation process.

Note

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Interview questions and protocol

1. Background information

- Information about the firm
- Information about the interviewee's position, experience in the industry and the firm, and major responsibilities.

2. Brief introduction to the research project: We are trying to get a sense of how business intelligence and analytics use process results in insight generation, and hence in value creation.

Questions were as follows:

a What is your understanding of business intelligence and analytics? How would you describe it in your words?
b To ensure a common understanding of the term, we suggest the following theory-based definition: "Business intelligence and analytics (BI&A) refer to the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen et al., 2012, p. 1166). How do you agree? Which BI&A techniques you widely use in your organization?
c How does BI&A use results in insight generation in your organization?
d How do you use BI&A generated insights?
e What are the specific technological requirements to gather and process data into valuable knowledge?
f What human skills requirements need to be met for BI&A facilitated knowledge generation?
g What organizational factors influence the value creation process?
h What are the main problems that you have witnessed or heard about?
i Thinking back over your remarks-Are there any other issues that we have not discussed and that you find worrisome? Anything else of importance you want to add?

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