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THE RELATIONSHIP BETWEEN BUSINESS INTELLIGENCE AND ANALYTICS USE AND ORGANIZATIONAL ABSORPTIVE CAPACITY: APPLYING THE DELONE & MCLEAN INFORMATION SYSTEMS SUCCESS MODEL

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ABSTRACT: *Building on the DeLone and McLean Information Systems (IS) success model and the knowledge-based theory of absorptive capacity, this paper examines the role of the business intelligence and analytics (BI&A) use for enhancing a firm's absorptive capacity for knowledge creation. We collected survey data from an online and mail-delivered survey questionnaire with 97 respondents at the organizational level in the Slovenian medium- and large-sized firms from several industries. The results from the partial least squares SEM showed that the BI&A use relates significantly to absorptive capacity enhancement, thus fostering knowledge creation. Moreover, information quality and system quality are positively linked with BI&A use at the organizational level.*

Key words: *Business intelligence and analytics use, DeLone and McLean IS success model, absorptive capacity, knowledge creation*

JEL classification: M12

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1 INTRODUCTION

The last decade has witnessed accelerated growth in investment in business intelligence and analytics (BI&A). Following the Chen, Chiang, and Storey (2012) definition, firms use BI&A techniques, technologies, systems, and applications to analyse business and market data and information to derive better and timely business decisions. BI&A encompasses many advanced analytics techniques, such as data mining, machine learning forecasting, semantic analysis, network analysis, and neural networks (Arnott & Pervan, 2014). Gartner's (2013) survey on IT spending found that BI&A continues to be one of the top priorities for the most successful firms, hence many authors have become interested in measuring the payoffs realized in terms of enhanced organizational performance and

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increased organizational value (Beath, Becerra-Fernandez, Ross, & Short, 2012; Côte-Real, Oliveira, & Ruivo, 2017; Elbashir, Collier, Sutton, Davern, & Leech, 2013; Hsieh, Rai, & Xu, 2011). It is evident, however, that significant differences among studies exist regarding the measurement and examination of the technology's benefits and costs. Many organizational-level studies have observed positive organizational benefits from BI&A investments (Davenport, 2006; Elbashir et al., 2013; Trkman, McCormack, De Oliveira, & Ladeira, 2010), while a large body of research indicates that organizations have failed to reap organizational benefits from using BI&A or detects no significant advantage from using BI&A (Chen, Chen, & Bajwa, 2016; Ransbotham, Kiron, & Prentice, 2016; Torres, Sidorova, & Jones, 2018).

Despite the prominence of BI&A as a source that yields organizational benefits, very few studies have examined BI&A's value creation process (Fink, Yogev, & Even, 2016; Trieu, 2017; Vidgen, Shaw, & Grant, 2017). Existing research has examined BI&A's success predominantly from a technological point of view (Bose, 2009; Chaudhuri, Dayal, & Narasayya, 2011; Chen et al., 2012; Hackney, Dooley, Levvy, & Parrish, 2015). However, the success of some information systems is often indirectly influenced by different organizational, human, and environmental factors, making success measurement generally complex. Unsurprisingly, some authors have called for moving beyond traditional financial measures, such as return on investment (ROI), market share, profitability, and sales growth, to better understand and explore both the tangible and intangible benefits of BI&A use (Fink et al., 2016; Sharma, Mithas, & Kankanhalli, 2014; Trieu, 2017; Yeoh & Popovič, 2016). To date, nonetheless, little attention has been given to improving the understanding of the role of BI&A in creating intangible organizational benefits, such as knowledge, organizational capabilities, and customer relationship management (Elbashir et al., 2013; Fan, Lau, & Zhao, 2015; Işık, Jones, & Sidorova, 2013; Sangari & Razmi, 2015; Shollo & Galliers, 2016; Yeoh & Popovič, 2016).

Acknowledging the great need to understand the association of the BI&A use with the intangible organizational benefits, the following research questions were addressed: (1) What are the appropriate dimensions for evaluating the success of BI&A in knowledge creation at an organizational level? (2) What is the role of the BI&A use in enhancing a firm's absorptive capacity for knowledge creation? To provide a comprehensive answer to these questions, we developed a theoretical model that relies on the DeLone and McLean IS success model (DeLone & McLean, 1992, 2003) and the knowledge-based theory of absorptive capacity (Lane, Koka, & Pathak, 2006; Zahra & George, 2002), applied to the context of BI&A. This paper, therefore, offers a twofold contribution to the BI&A and IS management research areas. Firstly, to the best of our knowledge, this is the first time that the DeLone and McLean model has been combined with the theory of absorptive capacity to develop and test a BI&A success model focusing on enhancing knowledge creation. Secondly, this research examines BI&A use not only from a rate-recurrence view but also regarding the nature of its use for fully capturing the BI&A use dimension. Hence, according to Seddon (1997) discussion, we apply BI&A use as a proxy variable for the benefits from use. Instead of assuming a pure, positive relationship between the time spent

using BI&A and the benefits it provides, we considered the nature of the use to play an important role in providing benefits as well.

In what follows, the paper starts with the theoretical foundation of the presented conceptual model for the BI&A success. Next, a set of hypotheses is developed, examining the interplay between the dimensions of the presented model. Following this, the research methodology and data analysis using partial least squares SEM are presented. The paper concludes by discussing the theoretical contributions and practical implications of the research, in addition to addressing limitations and providing suggestions for future research.

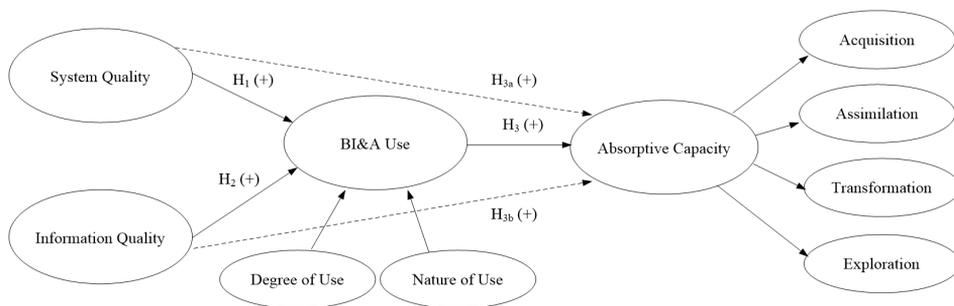
2 THEORETICAL FOUNDATION

Much research has been done to explain what makes some BI&A systems successful. For instance, the technology acceptance model (TAM) (Davis, 1989) is often applied to explain the intention to use and the readiness to accept the systems (Foshay & Kuziemsky, 2014; Popovič, Coelho, & Jaklič, 2009). Acceptance, however, is not equivalent to usage and success, thus the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003) is often used to supplement the behavioural intent to use with the usage behaviour (Grublješič & Jaklič, 2015b). Moreover, the task-technology fit theory (Goodhue & Thompson, 1995) and technology–organization–environment (TOE) framework (Depietro, Wiarda, & Fleischer, 1990) have been used to explain how certain organizational capabilities and the environment influence the acceptance and use of technology (Burnay, Jureta, Linden, & Faulkner, 2016; Grublješič & Jaklič, 2015a). Nevertheless, the DeLone and McLean IS success model (DeLone & McLean, 1992, 2003) has been widely applied in the existing literature to describe how system quality, information quality, and service quality affect individual or organizational performance, BI success, or decision-making processes (Hou, 2012; Kokin & Wang, 2014; Popovič et al., 2009; Popovič, Hackney, Coelho, & Jaklič, 2012; Wieder & Ossimitz, 2015).

In the current research, we focus on the organizational benefits of the BI&A use by applying the DeLone and McLean IS success model. This model has been found to be a useful framework for understanding, describing, and measuring the IS success and is one of the most often employed and cited models. The model identifies several variables of the IS success: information quality, system quality, service quality, use, user satisfaction, and net benefits. Although value (or net benefits) is the dependent success variable, system use is crucial for net benefits to occur. Moreover, the original D&M model (1992) demonstrated a good fit for measuring the IS success compared to other model re-specifications (Rai, Lang, & Welker, 2002; Sedera & Gable, 2004). Likewise, many meta-analyses have examined and validated different relationships in the D&M model (Bokhari, 2005; Mahmood, Hall, & Swanberg, 2001; Sabherwal, Jeyaraj, & Chowa, 2006). Respectively, the DeLone & McLean IS success model has often been used as the theoretical basis with which to evaluate the BI&A success. Hence, a diverse application can be found. For instance, the model has been extensively applied for investigating the relationship between the end-user satisfaction,

BI&A use, and financial performance (Hou, 2012; Kokin & Wang, 2014), further, for investigating the relationship between the information, system, and service quality on one hand and the user satisfaction and use on the other (Daradkeh & Moh'd Al-Dwairi, 2018; Gaardboe, Nyvang, & Sandalgaard, 2017; Gonzales, Wareham, & Serida, 2015), and lastly, for the investigation of the relationship between the managerial-decision making quality, user-satisfaction, and organizational performance (Wieder, Ossimitz, & Chamoni, 2012). Since some variables of the IS success have demonstrated unstable relations with the other variables included in the DeLone and McLean IS success model, such as the user satisfaction with use and further use with individual impact, D&M was applied as a guiding framework and other organizational factors included in the model. Moreover, service quality was not incorporated as a success dimension, since it was not part of the original model and has often been criticized as irrelevant (Seddon, 1997). Therefore, the conceptual framework of this research is presented in Figure 2 1.

Figure 2-1. *Proposed conceptual model: Adapted DeLone and McLean BI&A success model*



Note: Dotted lines represent hypotheses regarding mediation (indirect) effects via BI&A use

2.1 Business intelligence and analytics use

In line with the existing IS literature, we define the BI&A use as the degree to and the manner in which BI&A is utilized by organizations (Petter, DeLone, & McLean, 2008). Empirical studies have adopted multiple long-standing measures of use, including the frequency of use, extent of use, amount of use, appropriateness of use, and self-reported use. However, many authors have criticized the use of the self-reported, rate recurrence-based measures of use and called for measures that integrate different aspects of usage and are more contextualized, complete, and valid (Burton-Jones & Straub Jr, 2006; Petter, DeLone, & McLean, 2013). The system use represents an appropriate measure of success however only when properly capturing the relationship between the use and expected outcomes. Measuring the frequency and intensity of use without considering and capturing the nature of the use is deficient (Doll & Torkzadeh, 1998). For this reason, we measured the BI&A use as the use of information from the BI&A system regarding the extent, frequency, and

nature of use (DeLone & McLean, 2003, Burton-Jones & Straub, 2006). Since the expected outcome is enhanced knowledge creation, the BI&A system should allow organizations to monitor the market, competition, and consumers, easily track the sources of internal and external knowledge, search for, generate and store knowledge, and easily retrieve and use the stored knowledge (Gold, Malhotra, & Segars, 2001; Shollo & Galliers, 2016).

Nevertheless, following Burton-Jones and Gallivan (2007), we examined use from a higher-level perspective, that is at the organizational level. As Doll and Torkzadeh (1998) suggested, we used the BI&A use as the central construct in the system-to-value chain that links the system use antecedents with the organizational impact of information technology. BI&A is therefore a mediating variable leading to downstream impact on benefit organizations (DeLone & McLean, 1992; Goodhue, 1995). Following the DeLone and McLean (1992) model, we considered the information quality and system quality to be antecedent constructs to the BI&A use. Both prove to be equally important since even a high-quality system can produce worthless results if the generated information is of low quality (inadequate or wrong). In addition, we view success not simply as the system being used but rather as its contribution to knowledge creation.

2.2 System quality and BI&A use

System quality is defined as the desirable characteristics of an information system. The perceived ease of use has often been implemented as a measure of system quality within the TAM-related research (Davis, 1989), although it does not fully capture the system quality construct. As a response researchers have developed measurement instruments that capture diverse system quality dimensions, such as reliability, effectiveness, maintainability, ease of learning, intuitiveness, sophistication, flexibility, response time, accessibility, and integration (Nelson, Todd, & Wixom, 2005; Petter et al., 2008; Rivard, Poirier, Raymond, & Bergeron, 1997). We conceptualized system quality as a construct measured by dimensions of reliability, flexibility, accessibility, response time, and integration (DeLone & McLean, 2016; Petter et al., 2008; Wixom et al., 2014; Wixom & Watson, 2001). Hence, reliability is the degree to which a system is trustworthy and performs consistently well, while flexibility refers to the ability to adapt and customize the system to users' changing demands. Further, accessibility refers to the ease with which information can be accessed, integration refers to the degree to which the system allows integration with various data sources, and response time refers to the length of time a system needs to respond to a request for action or information.

The relationship between the system quality and the IS system use has been differently described in the existing literature (Nguyen, Nguyen, & Cao, 2015; Urbach & Müller, 2012). For instance, Fitzgerald and Russo (2005) and Caldeira and Ward (2002) found support for it, while Gill (1995) found this relationship to be insignificant, and Weill and Vitale (1999) with Premkumar and King (1994) found that the system quality can negatively

affect the system use when the information system is complex and incompatible with the existing hardware and software.

Organizations should ensure good system quality to reap the full benefits of the BI&A use. This includes upgrading and customizing the existing BI&A infrastructures and architectures to fit the changing data requirements (Chen et al., 2012). Examples include upgrading traditional data warehouses and data marts to Hadoop database technology and customizing advanced analytics tools, such as data mining and natural language processing. In addition, the system should allow integration with a variety of data sources, especially with the new developments in the “big data” era (Chen & Zhang, 2014). Long response time could be an important obstacle that leads to the BI&A underuse (Gandomi & Haider, 2015). Nonetheless, the system should allow easy access to relevant information to anyone who needs them, regardless of their training (Boyd & Crawford, 2012). Accordingly, the first hypothesis is as follows:

H₁: System quality is positively associated with BI&A use.

2.3 Information quality and BI&A use

Information quality is on the other hand about the system output's desirable characteristics. However, information quality is often not distinguished as a unique construct and is measured as a dimension of user satisfaction (Doll, Xia, & Torzadeh, 1994; McKinney, Yoon, & Zahedi, 2002; Rai et al., 2002). Accordingly, many authors have developed scales via their review of the information quality literature relevant to the type of the IS under study (Fraser & Salter, 1995; Gable, Sedera, & Chan, 2003; Wixom & Watson, 2001). Hence, dimensions such as relevance, completeness, conciseness, accuracy, timeliness, usability, and understandability are often used to describe information quality (DeLone & McLean, 2016; Lee, Strong, Kahn, & Wang, 2002; Nelson et al., 2005; Wixom et al., 2014). Following Nelson et al. (2005), we shaped information quality by using four dimensions: completeness, accuracy, format and currency. Accordingly, completeness represents the degree to which all possible elements are represented in the stored information, further, accuracy is the degree to which the user recognizes that same information as correct and unambiguous, while format represents the degree to which information is presented in an understandable and interpretable manner to the user, and currency represent the user's perception of the degree to which the information is up-to-date.

The existing literature has found mixed support for the relationship between the information quality and system use (Petter et al., 2013). For example, some authors found support for information quality in that it is an important antecedent of the system use or intention to use (Fitzgerald & Russo, 2005; Halawi, McCarthy, & Aronson, 2008; Kositanurit, Ngwenyama, & Osei-Bryson, 2006). On the other hand, Goodhue and Thompson (1995) found some of the characteristics of information quality to be significantly related to usage, but also some

that are not. Furthermore, certain studies have found an insignificant relationship between the information quality and intention to use (Iivari, 2005; McGill, Hobbs, & Klobas, 2003).

BI&A systems are increasingly being used to provide decision-makers with a real-time, rich market and consumer data for better decision-making and action-taking (Kowalczyk & Buxmann, 2014; Lavallo, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). However, BI&A analyses can often provide very limited scope and quality, namely, the information must have good predictive power along with high degrees of completeness and accuracy, leading to confident acting upon the information (Dhar, 2013). Moreover, decision-makers need real-time information that will allow them to adjust their actions on a continuous basis, especially in a high-velocity market (Eisenhardt & Martin, 2000). Thus, as discussed by Kowalczyk and Buxmann (2015), the information insufficiency regarding incompleteness, inconsistency, inaccuracy, irrelevance, and unreliability can limit the decision-making ability, affecting the success of BI&A use. Moreover, decision-makers can revert to intuitive decision-making (Matzler, Bailom, & Mooradian, 2007; Ransbotham et al., 2016). Nonetheless, presenting the information in the form of visualizations and graphs facilitates the interpretation of new information and the further use of the system (Lavallo et al., 2011; Yeoh & Popovič, 2016). As such, our second hypothesis is:

H₂: Information quality is positively associated with BI&A use.

2.4 BI&A use and absorptive capacity

In the literature, the BI&A use has been reported to yield different organizational benefits. Therefore, a variety of measures of organizational impact can be observed, such as improved organizational performance and overall success (Boyd & Crawford, 2012; Davenport, Barth, & Bean, 2012; Elbashir, Collier, & Davern, 2008; Kiron & Shockley, 2011; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Shuradze & Wagner, 2016), business process change (Arnold, 2006), innovation of new business models, products, and services (Bughin, Livingston, & Marwaha, 2011; Fisher, DeLine, Czerwinski, & Drucker, 2012; Lavallo et al., 2011; Manyika et al., 2011), support and enhancement of collaboration and decision-making (Chen et al., 2012; Kowalczyk & Buxmann, 2014; Kowalczyk, Buxmann, & Besier, 2013), and also knowledge creation and learning (Holsapple, Lee-Post, & Pakath, 2014; Shollo & Galliers, 2016; Siemens & Long, 2011). Although this body of research has theoretically advanced the understanding of the BI&A's success, it nevertheless offers a limited understanding of the knowledge-creation process that delivers value, which calls for further research. Hence, we propose that the BI&A use facilitates absorptive capacity processes and enhances knowledge creation (Roberts, Galluch, Dinger, & Grover, 2012).

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 a commercial end." It all depends on the prior related knowledge which helps firms to better evaluate the signals for technological

advances and development. Absorptive capacity, therefore, allows an organization to identify new outside knowledge and to assimilate and integrate that knowledge with the existing knowledge internally (Kogut & Zander, 1992). Prior studies have shown the underlying absorptive capacity's capabilities of external knowledge acquisition and assimilation (potential absorptive capacity), as well as further transformation to new knowledge and exploitation (realized absorptive capacity) to be an important component of dynamic capabilities (George, 2005; Malhotra, Gosain, & El Sawy, 2005; Verona & Ravasi, 2003; Wang & Ahmed, 2007; Zahra & George, 2002). On that account, knowledge acquisition refers to the organization's ability to identify and obtain information through external sources, while knowledge assimilation is the organization's ability to analyze, interpret and understand the acquired information. Further, knowledge transformation is about facilitating the combination of existing knowledge with the new knowledge as well as its internalization, whereas knowledge exploitation is the application of the transformed knowledge to commercial ends (Flatten, Engelen, Zahra, & Brettel, 2011). Accordingly, absorptive capacity in itself is captured by capabilities that reflect dynamic processes (Flatten et al., 2011; Lane et al., 2006). Moreover, absorptive capacity not merely connects the underlying knowledge capabilities, but combines and integrates them, creating synergistic outcomes, hence, it might be observed as a second-order dynamic capability where absorptive capacity is more than the sum of the underlying knowledge capabilities (Grant, 1996; Lichtenthaler, 2009; Raisch & Birkinshaw, 2008). In this way, absorptive capacity plays an important role in improving firm ability to develop dynamic capabilities and prevent core capabilities from becoming core rigidities (Kang & Snell, 2009; Leonard-Barton, 1995; Teece, Pisano, & Shuen, 1997).

BI&A is predominantly viewed as an information processing tool that provides knowledge infrastructure and knowledge process capabilities, such as acquisition, transformation, application of knowledge, which enhance an organization's existing knowledge base, and in turn increases organizational absorptive capacity (Gold et al., 2001; Srivardhana & Pawlowski, 2007). Moreover, BI&A use facilitates knowledge acquisition through identification, collection, and analysis of external data and information. Hence, the quality of information provided by the BI&A system is an important driver of the use behaviour. Unsatisfactory information quality could arouse doubts about the reliability of the BI&A, which in turn could harm the use behavior and vice versa. Next, the knowledge-acquisition process is enhanced by an advanced analysis of the vast amount of data and information collected in the previous process. In addition, the interpretation of information is assisted through different visualization techniques (Minelli, Chambers, & Dhiraj, 2012). BI&A supports the combination of new, assimilated knowledge with the prior knowledge based on advanced database technologies and parallel, distributed algorithms (McAfee et al., 2012). It is important, however, to ensure sufficient system quality, leading to increased trust in the ability of the system to assist knowledge creation and ultimately to a willingness to use (Saeed, Hwang, & Mun, 2003). Also, BI&A supports the dissemination of, search for, and reuse of the transformed knowledge to aid further improvement of business processes, products, and services (Kowalczyk & Buxmann, 2015). Therefore, we hypothesized the following:

H₃: The BI&A use is positively associated with organizational absorptive capacity.

H_{3a}: The positive association of system quality with organizational absorptive capacity is mediated by the BI&A use.

H_{3b}: The positive association of information quality with organizational absorptive capacity is mediated by the BI&A use.

3 RESEARCH METHODOLOGY

3.1 Sampling, data collection, and sample properties

To test the model and the related hypotheses, we surveyed Slovenian organizations from several industries. As recommended by Moore and Benbasat (1991), the survey instruments drew upon a comprehensive literature review, and all of the constructs were operationalized through an existing measurement scale that has been validated in the extant literature. To ensure content validity, we asked five academic IS and management researchers to review and assess the content, scope, and purpose of the survey (Lawshe, 1975; Lynn, 1986). We modified some of the questionnaire items to properly tap into the study's specific context and simplify interpretation. The questionnaire was developed and disseminated in English to ensure identical meanings.

The data for this research were acquired from a web-based and mail surveying tool in 2018. Two screening criteria were used to guarantee the quality of the data: (1) the respondent had deep knowledge of the organization's management, and (2) the respondent had more than three years of experience in the BI&A initiatives and held a management, executive, or IT position in the firm. The Strategic Research Innovation Partnership (SRIP) MOBILITY ACS+ and Purchasing Association of Slovenia provided us with access to their internal mailing databases. The data were supplemented by the database of the top 101 most successful Slovenian firms in 2016. Hence, the initial sample of 500 firm representatives from the mailing list received an e-mail invitation to participate in the web-based survey.

We received 36 valid responses in the first round. To increase the response rate, we sent follow-up e-mails and offered to send them the survey by mail. During the following month, we received 61 additional valid responses, totalling in 97 usable responses (overall response rate of 19.4%). Table 1 shows the sample's descriptives. The final sample consisted mostly of medium (53.6%) and large organizations (38.1%), according to the current EU guidelines (European Commission, 2005). The latter sample comprises different industry sectors in line with the NACE classification, of which almost 70% were from the manufacturing, wholesale and retail trade, transport, storage, and communication sectors. Regarding the respondents' positions, IT and business executives were almost equally represented.

3.1.1 Outliers and bias examination

We examined the collected data for missing data, suspicious response patterns, and outliers (Hair, Hult, Ringle, & Sarstedt, 2017). First, we removed three observations in which straight-lining or a high proportion of missing data (>15%) was detected. After excluding the problematic observations, we used a dataset of 97 responses in all of our analyses. Since the amount of the missing data per indicator was less than 5%, we applied a mean value replacement to handle the missing data. We used the IBM SPSS Statistics to test for outliers. Using box plots and stem-and-leaf plots, few outliers were found, however, since there was no clear explanation for the exceptional values, we retained them for further analysis (Sarstedt & Mooi, 2014). Further, following the Hair, Hult, et al. (2017) recommendation, we examined the data distribution regarding skewness and kurtosis. Although most of the data per indicator were normally distributed, some data exhibited skewness and kurtosis greater than +1, thus indicating non-normal distribution.

We assessed a potential non-response bias by using a wave analysis, in which the respondents were grouped into early- and late-respondent groups, and their sample distributions compared with the Kolmogorov-Smirnov test (Armstrong & Overton, 1977). Our analysis showed no significant differences (5% significance level, $p > .05$) between the early- and late-respondent groups regarding organizational attributes such as firm size (χ^2 test, $p = 2.255$) and return on investment (χ^2 test, $p = .427$). Thus, no evidence of response bias was found.

Table 1. *Sample descriptives*

Sample characteristics (n = 97)	Obs.	(%)
Respondent position		
IT executive		45.4
Chief information officer (CIO)	8	8.2
IT manager	30	30.9
BI manager	6	6.2
Business executive		54.6
Chief executive officer (CEO)	27	27.8
Chief financial officer (CFO)	2	2.1
Other business executives	24	24.7
No. of employees		
<50	8	8.2
50–250	52	53.6
>250	37	38.1

Sample characteristics (n = 97)	Obs.	(%)
Industry		
Agriculture, forestry, hunting	2	2.1
Manufacturing	33	34.0
Electricity, gas, water supply	8	8.2
Construction	1	1.0
Wholesale and retail trade	18	18.6
Hotels and restaurants	1	1.0
Transport, storage, and communication	16	16.5
Financial intermediation	4	4.1
Real estate, renting and business activities	6	6.2
Education	1	1.0
Health and social work	1	1.0
Other	6	6.2

Moreover, as within the study a single-respondent research design was used and the responses were self-reported, we assessed the common method variance (CMV) biases for the sake of validity (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In order to diagnose and control for CMV biases, three approaches were employed. First, we used the Harman's *ex-post* single-factor analysis. The factorial analysis showed that no single factor accounted for the majority of the covariance among the measures, with the first extracted factor accounting for 35.743% of the variance. Hence, the common method bias is unlikely to be an issue in this study. Second, we applied the Rönkkö and Ylitalo (2011) six-step marker variable approach to control for CMV in PLS. Since the factor structure of the marker items is not important in itself as long as the marker constructs are mostly uncorrelated with the rest of the study constructs (Rönkkö & Ylitalo, 2011), the marker indicators were a combination of two partial scales of environmental dynamism (Dill, 1958; Volberda & Van Bruggen, 1997) and environmental competitiveness (Birkinshaw, Hood, & Jonsson, 1998; Jaworski & Kohli, 1993). The results presented in Table 8 (Appendix B) show no remarkable differences between the baseline model and the model with the marker variable, while all paths maintained their level of statistical significance, indicating no method variance problem. Also, we adopted the full collinearity assessment approach (Kock, 2015) and found that all factor-level VIF values ranged from 1.277 to 2.051, i.e. all below the recommended threshold of 3.3. (Diamantopoulos & Siguaaw, 2006). Thus, the traditional single-factor test, the marker variable test, and the full collinearity assessment approach provided support in that the common method bias was not a significant threat to the validity of our study.

3.2 Structural equation modelling approach

Two methods are available to researchers for estimating structural equation models by means of empirical data: (1) covariance-based SEM techniques (CB-SEM) (Jöreskog, 1978; Jöreskog & Sörbom, 1982) and (2) variance-based partial least squares (PLS-SEM) (Chin, 1998; Hair, Hult, et al., 2017; Lohmoller, 1988). Following the Hair, Sarstedt, Ringle, and Mena (2012) and Ringle, Sarstedt, and Straub (2012) arguments for selecting an appropriate method for the SEM estimation, our study relies on the PLS-SEM method. The model includes complex second-order latent variables as well as mediation, for which adopting the PLS-SEM approach is considered to be a better choice (Hair et al., 2012). Moreover, the PLS-SEM approach is particularly suitable when a combination of reflectively and formatively measured latent variables are part of the structural model. Furthermore, not all of our indicator variables met the requirement for normal data distribution. Our analysis showed that some of our data variables were non-normal but not excessively non-normally distributed, providing an additional rationale for adopting PLS-SEM (Gefen, Straub, & Boudreau, 2000). Nonetheless, PLS-SEM has been established as particularly useful when analysing relatively small sample sizes in medium and high-complexity model setups (Reinartz, Haenlein, & Henseler, 2009). However, following Ringle, Wende, and Becker (2015) and Hair, Hult, et al. (2017), we determined the required sample size using power analyses. In our model, the maximum number of arrows pointing at a construct is five. Assuming the commonly used level of statistical power of 80%, we therefore needed at least 45 (or 58 in *G*Power* analysis) data sets to detect the R^2 values of at least 0.25 (with a 5% probability of error). Hence, the acquired 97 data sets met the data sample size requirements and were used to assess the proposed model in the SmartPLS 3 software (Ringle et al., 2015).

3.3 Operationalization of the constructs

In this study, two types of latent variables, namely reflective and formative, are employed. We used the information quality and system quality success variables as desirable characteristics and important antecedents of the BI&A use (DeLone & McLean, 2003, 2016). As discussed in section 2.2, system quality focuses on the impact of the system quality dimensions on the BI&A use and is measured by the dimensions of reliability, flexibility, accessibility, response time, and integration (DeLone & McLean, 2016; Petter et al., 2008; Wixom et al., 2014; Wixom & Watson, 2001). On the other hand, information quality focuses on the quality of the BI&A output and is frequently conceptualized as a multi-dimensional concept measured by various dimensions, such as completeness, accuracy, format, and currency (DeLone & McLean, 2016; Lee et al., 2002; Nelson et al., 2005; Wixom et al., 2014). Therefore, to measure the system quality and information quality, we adopted a measurement scale developed and tested by Nelson et al. (2005) and deemed valid and reliable. Both system and information quality were operationalized as formatively measured latent variables since all of the indicators capture a specific aspect of the constructs' domain and cause the constructs themselves, of which both were explored at the organizational level. Table 4 represents all items adapted from the literature used.

For the purpose of measuring the BI&A use, we applied hierarchical component models (HCMs). The link between the lower-order components (LOCs) and higher-order components (HOCs) was characterized as a reflective-formative type relationship, which allowed for a more parsimonious PLS model. Since the latent variable of the BI&A use was operated at the organizational level, we employed the intensity, frequency, and nature/purpose of use to measure the degree and manner in which organizations utilize BI&A, as discussed by Petter et al. (2013). The degree of use was reflectively measured by the frequency and intensity measures adapted from Venkatesh, Brown, Maruping, and Bala (2008). Frequency was measured on a 7-point scale ranging from “does not use” to “almost always,” while the intensity of use was also measured on a 7-point scale ranging from “not at all” to “a very great extent.” Regarding the nature/purpose of use, we adapted a measurement scale developed and tested by Gold et al. (2001). Hence, the nature of use was operationalized as a reflectively measured latent variable. All items were measured using a 7-point scale ranging from “strongly disagree” to “strongly agree.”

Following the Gao, Yeoh, Wong, and Scheepers (2017) research findings, we used absorptive capacity as a dependent variable, since the aim of the research involved knowledge-creation and sharing. To measure absorptive capacity, we adopted a measurement scale developed and tested by Flatten et al. (2011), which relies on the absorptive capacity definition of Zahra and George (2002). Once again, we used a hierarchical component model to measure the latent variable of absorptive capacity. Knowledge acquisition, assimilation, transformation, and exploitation were applied as lower-order components. Hence, a reflective-reflective type of HOC with the mode A approach was applied, reducing the level of collinearity among the indicators and increasing the model's parsimony. All of the items were measured on a 7-point Likert scale ranging from “strongly disagree” to “strongly agree.”

4 RESULTS

4.1 Measurement model

We modelled the constructs of assimilation (ASS), acquisition (ASQ), transformation (TRF), exploitation (EXP), degree of use (DEGUSE), and nature of use (NATUSE) as measured reflective constructs. Further, we modelled the information quality (INFQ) and system quality (SYSQ) as formatively measured constructs since they are not interchangeable and are not expected to co-vary within the same latent construct (Petter, Straub, & Rai, 2007). In addition, we modelled the absorptive capacity (ACAP) as a reflective-reflective second-order construct, with ASS, ASQ, TRF, and EXP as lower-order constructs (Flatten et al., 2011), and used the repeated indicator approach with mode A on the higher-order construct, following the Becker, Klein, and Wetzels (2012) recommendation. Moreover, we modelled the business intelligence and analytics use (BIA_USE) as a reflective-formative, second-order construct, with NATUSE and DEGUSE as lower-order constructs. Hence, for BIA_USE, we followed the Becker et al. (2012) recommendation and used the repeated indicator approach with mode B on the higher-order construct and an inner path

weighting scheme, since this specification was found to be the most appropriate for an unequal number of items among the first-order reflective constructs. Detailed procedures and the results of the measurement validation are presented in the continuation.

4.1.1 Reflective measurement

The PLS-SEM model assessment initially focuses on the evaluation of the reliability and validity of the construct measures (Gefen & Straub, 2005; Ringle et al., 2012). Our reflectively measured constructs were tested for the indicators of reliability, construct reliability, convergent validity, and discriminant validity (Ringle et al., 2012). Based on our assessment of the indicator reliability, we removed three items (TI1, TI3, TI5) which increased the average variance extracted to above the threshold (Hair, Hult, et al., 2017). As Table 5 reveals, the indicators in the reflective measurement models reached satisfactory indicator reliability, since all of the reflective indicators had an outer loading of above 0.708, and two indicators exhibited slightly lower loadings of 0.694 and 0.691. Also, the reflective measurement model achieved a composite reliability of 0.791 or higher, suggesting reliability of the construct measures' internal consistency. To test the convergent validity, we used the average variance extracted (AVE) and found acceptable values of 0.5 or higher, as the construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981; Henseler, Ringle, & Sinkovics, 2009). For the higher-order reflective-reflective construct of absorptive capacity (ACAP), we calculated the AVE and composite reliability manually, following Hair, Hult, et al. (2017) guidelines. Finally, we used two measures to assess the constructs' discriminant validity. First, according to the Fornell and Lacker (1981) criterion, the square root of each construct's AVE was to be higher than the correlations with other latent variables. Second, we examined the indicators' cross-loadings, which were supposed to not reveal any indicators with higher loading on another construct (Chin, 1998). Both analyses indicated that the constructs exhibit discriminant validity. Finally, we applied the heterotrait-monotrait ratio (HTMT) criterion and found that all of the values were lower than the conservative threshold value of 0.85 (Hair, Hult, et al., 2017), thus indicating the establishment of discriminant validity. In addition, we ran bootstrapping to test whether the HTMT values were significantly different from 1, clearly favouring the discriminant validity of the constructs. However, the discriminant validity between the higher- and lower-order constructs of absorptive capacity could not be established, which is expected because the measurement model of the higher-order construct repeats the indicators of the lower-order constructs. Based on the above findings, it is concluded that all of the reflective construct measures were valid and reliable.

4.1.2 Formative measurement

For our model two first-order formative constructs were proposed, namely information quality (INFQ) and system quality (SYSQ). To evaluate the formative measurement models, we started by assessing the outer collinearity. In formative measurement, excessive multicollinearity between the constructs is undesirable because it can destabilize the

model and lead to redundant items (Diamantopoulos & Winklhofer, 2001). Therefore, we examined the variance inflation factor (VIF) scores for the formative measures and found values that were uniformly below the threshold value of 3.3 (Diamantopoulos & Siguaw, 2006), indicating that multicollinearity is not an issue for the estimation of the PLS path model. Next, we assessed the relevance and significance of the indicators' weights. Looking at the significance level of the outer weights, we found that all of the formative indicators were significant at the 5% level, except for INFQ2, INFQ3, SYSQ3, SYSQ4, and SYSQ5. However, following the Hair, Hult, et al. (2017) recommendations, we retained all indicators of the formative constructs, since all of the outer loadings were significant at a 5% level. Moreover, prior research and theory also support the relevance of these indicators in capturing information quality and system quality dimensions (Gorla, Somers, & Wong, 2010; Nelson et al., 2005; Saeed & Abdinnour-Helm, 2008). We report the bias-corrected bootstrap confidence interval for additional information on the stability of the coefficient estimates. Moreover, we used the Cadogan and Lee (2013) and Hair, Sarstedt, Ringle, and Gudergan (2017) guidelines to assess the effect of the antecedent constructs (information quality and system quality) on the formative second-order construct of BIA_USE through its lower-order constructs (DEGUSE and NATUSE). We observed that among the two lower-order constructs, NATUSE had a stronger effect on business intelligence and analytics use (0.781 for NATUSE and 0.364 for DEGUSE) and thus greater relevance for forming BIA_USE. Among the BIA_USE's antecedents, INFQ (0.436) had a stronger effect than SYSQ (0.333). Moreover, at the second-order construct level, first-order constructs act as indicators for the second-order constructs. Therefore, their weights and significance (Table 10) were examined and the weights of both first-order constructs established to be higher than 0.10. In addition, their signs were consistent with the underlying theory (Andreev, Heart, Maoz, & Pliskin, 2009). Although the DEGUSE weight was not significant, the indicator was retained because theory strongly supports the relevance of this indicator in capturing the BI&A use (Popovič, Hackney, Coelho, & Jaklič, 2014; Trieu, 2017). The results suggest all of the formative measures demonstrated a satisfactory construct validity and also no significant multicollinearity. Considering that the results from the reflective and formative constructs exhibited satisfactory levels of quality, we proceeded with the evaluation of the structured model.

4.2 Structural model

To evaluate the structural model, we followed the Hair, Hult, et al. (2017) six-step procedure, namely the collinearity assessment, structural path coefficients, the coefficient of determination R^2 , effect size f^2 , predictive relevance Q^2 , and the effect size q^2 . We ran the PLS-SEM algorithm in SmartPLS 3, using the path weighting scheme and a stop criterion set at 10^{-7} , with 5,000 iterations of re-sampling and the *no sign change* option. The VIF values of all combinations of endogenous constructs and corresponding exogenous constructs were below the threshold of 3.3 (the highest VIF among the explanatory variables was 1.575). Thus, collinearity among the predictor constructs did not prove to be a critical issue in the structural model. To avoid bias toward complex models, we considered the adjusted R^2 values according to the number of exogenous constructs relative to the sample size

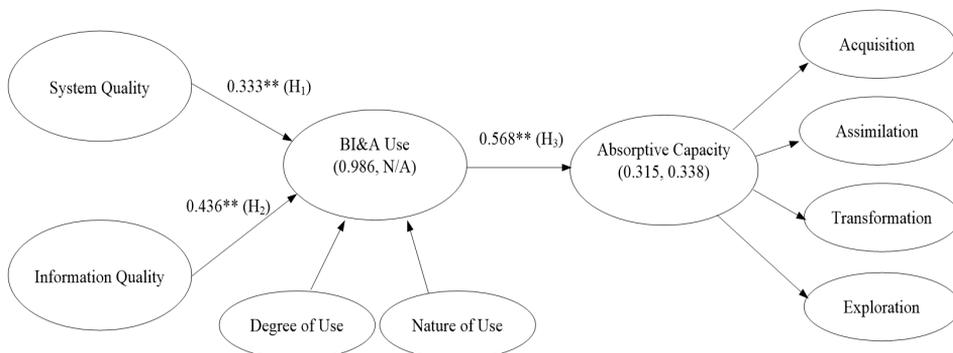
(Hair, Hult, et al., 2017). All of the dependent variables presented reasonable values. The f^2 values were calculated to evaluate whether an omitted construct had a substantive impact on the endogenous constructs, where only small and moderate effects were found present. For all reflective endogenous constructs we calculated the Stone–Geisser’s predictive relevance Q^2 , using the blindfolding procedure with an omission distance of 7 (Hair, Hult, et al., 2017). The values of all of the endogenous constructs were above zero, thus providing support for the model’s predictive relevance regarding the endogenous latent variables. Also, we manually calculated the effect sizes, q^2 (relative impact of predictive relevance), and found small and moderate effects present. The path coefficients, R^2 and Q^2 , are presented in Figure 4 1. Table 2 shows the results of the hypothesized relationships, t -values, standard errors, and effect sizes.

Table 2. Results of the structural model path coefficients

Structural path	Path coefficient (β)	Effect size (f^2)	Effect size (q^2)	Standard deviation	t -value	Bias-corrected 95% confidence interval	Conclusion
SYSQ \rightarrow BIA_USE	0.333**	N/A	N/A	0.102	3.274	[0.092; 0.504]	H1 supported
SYSQ \rightarrow DEGUSE	0.299**	0.092	0.062	0.106	2.823	[0.064; 0.480]	
SYSQ \rightarrow NATUSE	0.287*	0.063	0.030	0.115	2.506	[0.027; 0.477]	
INFQ \rightarrow BIA_USE	0.436**	N/A	N/A	0.105	4.161	[0.194; 0.596]	H2 supported
INFQ \rightarrow DEGUSE	0.443**	0.210	0.164	0.090	4.899	[0.236; 0.599]	
INFQ \rightarrow NATUSE	0.351**	0.105	0.047	0.111	3.171	[0.098; 0.538]	
BIA_USE \rightarrow ACAP	0.568**	0.229	0.056	0.079	7.206	[0.275; 0.667]	H3 supported

Note: *Significant at the .05 level; **Significant at the .01 level

Figure 4-1. Estimated model



Note: *Significant at the .05 level; **Significant at the .01 level; (R^2 adjusted, Q^2) given for endogenous constructs

The results presented in Figure 2 1 show that the conceptual model explained 31.5% of the variation in firm absorptive capacity. Both the system quality ($\beta = 0.436, p < .01$) and information quality ($\beta = 0.333, p < .01$) proved statistically significant in explaining the BI&A use. This way, both H_1 and H_2 are confirmed. Moreover, the BI&A use ($\beta = 0.568, p < 0.01$) was statistically significant in explaining absorptive capacity, thus supporting H_3 as well.

4.2.1 Mediation analysis

Our model hypothesized that the BI&A use would mediate relationships between system quality and absorptive capacity on one hand and between information quality and absorptive capacity on the other. We tested further for mediation following the approach outlined by Hair, Hult, et al. (2017). Consequently, to evaluate mediation bootstrapping was used instead of the Sobel test. We found that both indirect effects were significant since neither of the 95% confidence intervals included zero. Furthermore, we assessed the direct effects and found that both direct effects were statistically non-significant ($t = 0.377; p = .706$, and $t = 0.184; p = .854$). It was therefore concluded that the BI&A use mediated fully the SYSQ-to-ACAP and INFQ-to-ACAP relationships, thus supporting H_{3a} and H_{3b} .

Table 3. Mediation bootstrapping test: Significance analysis of the direct and indirect effects

	Direct effect	95% confidence interval of the direct effect	t-value	Indirect effect	95% confidence interval of the indirect effect	t-value	Conclusion
SYSQ → ACAP	0.050	[-0.207; 0.320]	0.377	0.190**	[0.046; 0.323]	2.617	H_{3a} supported
INFQ → ACAP	-0.025	[-0.280; 0.234]	0.184	0.235**	[0.070; 0.389]	2.849	H_{3b} supported

Note: **Significant at .01 level

5 DISCUSSION AND CONCLUSION

Many organizations have heavily invested in BI&A to enhance organizational performance and increase organizational value. This has led to an increase in the scholarly attention to understanding the mechanisms through which the BI&A use yields organizational benefits. While the extant research provides a relatively rich description of the possible net benefits/impacts of the BI&A use regarding financial benefits, we know correspondingly little about the role of the BI&A use in creating intangible organizational benefits, such as knowledge creation. In the present study, we sought to understand the relatively unexplored aspect of knowledge creation from the BI&A use, answering the Gao et al. (2017)'s call for a deeper investigation of this scarcely researched issue. We created a conceptual model that draws and integrates the DeLone and McLean IS success theory with the absorptive capacity theory for knowledge creation in order to understand the relatively unexplored aspect of knowledge creation as a result of the BI&A use.

5.1 Theoretical contributions

Prior studies of BI&A have already been built upon the DeLone, and McLean IS success theory for the purposes of evaluating the BI&A success (Gaardboe et al., 2017; Hou, 2012; Kokin & Wang, 2014). Although these studies include the idea of value creation through an intensive BI&A use, much less attention has been focused on another important aspect, namely how knowledge is created through the BI&A use. To understand this aspect, we hypothesized that the intangible organizational benefit of knowledge creation happens through the facilitation of absorptive capacity processes. Specifically, we argued that BI&A provide the technological infrastructure and knowledge-processing capabilities to complement the existing knowledge base which in turn enhances organizational absorptive capacity. Unlike the prior research that views the benefits of BI&A predominantly from a technological perspective (Hou, 2012; Kokin & Wang, 2014), through quantifiable financial measures (Davenport et al., 2012; Elbashir et al., 2008) our study instead sheds light on the specific role of BI&A to initiate knowledge creation. This is not to say the previous BI&A success models are not important simply because they do not, or at least not directly, lead to knowledge creation. While such knowledge is beneficial in the context of system adoption, organizational readiness evaluation, and assessment of the BI&A fit, it is less useful in the context of organizational knowing. Overall, our findings are consistent with the existing anecdotal evidence (Eom, 2014; Shollo & Galliers, 2016), but also extend the research by emphasizing how knowledge is created through the processes of knowledge acquisition, assimilation, transformation and exploration, as well as the active role of BI&A in these processes.

Further, the IS success scholars have often assumed a positive effect between the intensity of the BI&A use, as measured by the rate-recurrence measures, and the organizational benefits, but at the same time generally taking for granted that more use yields benefits itself, neglecting the nature of the use. Considering the criticism on this incompleteness of capturing the BI&A use dimension by the degree of use (Petter et al., 2008; Petter et

al., 2013), within our research the nature of the use is considered as well in order to fully capture the BI&A use dimension. By doing so, we provided an enrichment of the prior work on the topic and highlighted the need for including the nature of use as an important dimension explaining the BI&A use.

Apart from the role of BI&A in fostering knowledge creation, the BI&A system and information quality are significant determinants of organizational absorptive capacity through their intermediate effect on the BI&A use. The results of our research suggest that by providing greater reliability, flexibility, accessibility, response time, and easy integration with the existing systems, system quality can be an important catalyst of the process of knowledge creation (Boyd & Crawford, 2012; Chen & Zhang, 2014). Scholars suggest mixed support for the relationship between system quality and use (Fitzgerald & Russo, 2005; Gill, 1995; Nguyen et al., 2015), and within this research we established a positive association between system quality and the BI&A use, suggesting that organizations should ensure good system quality, especially with the new developments in the “big data” era, in which BI&A technologies, techniques, and applications need to be adjusted to the changing data requirements (Chen et al., 2012). Moreover, in highly dynamic markets, a flexible and fast response system positively impacts the perceived ease of use, thus preventing the BI&A underuse. Hence, easy access contributes to a more frequent and extended use of BI&A (Boyd & Crawford, 2012). However, the mediation analysis showed that high-quality systems should be aligned with the nature of use, as otherwise firms may be unsuccessful at reaping the full benefits from their investments. Moreover, the BI&A system should assure that on the one hand, the generated insights and knowledge are adequate, and that on the other hand, the system reduces the additional effort required for use and distributes the assimilated knowledge across the organization. This is in line with a part of the existing research in which organizations overemphasize the importance of instantaneously buying and installing high-quality BI&A systems without ensuring beforehand that the systems fit the nature of use and that their users are ready to use the system extensively (Ransbotham et al., 2016).

In addition, our study implies that information quality plays another important role in transforming insights into organizational knowledge that can further serve in decision-making. In the beginning, the current study hypothesized that information quality influences the knowledge creation processes of absorptive capacity through the degree and nature of the BI&A use. In the extant work on the BI&A success, it is exactly this association that has been understudied. Namely, we found that complete and accurate information presented in an understandable format can provide decision-makers with good grounds for action-taking and decision-making, which is in line with a part of the existing research (Kowalczyk & Buxmann, 2014; Lavallo et al., 2011). Nevertheless, more information is not necessarily beneficial for an organization, since an organization's information- and knowledge-processing capacity is limited (Simsek, 2009), and what is more, can be counterproductive when organizations face information overload (Koka & Prescott, 2002; Wales, Parida, & Patel, 2013). The results of the current study extend this line of inquiry by revealing that the good-quality information and insights provided from

BI&A in combination with the rich prior knowledge base may improve the process of identification of useful external information and their incorporation into further actions. In contrast, low-quality information distracts organizations, leading them to additional search and processing, consequently affecting negatively the knowledge creation processes.

5.2 Practical implications

Support for the BI&A use having a positive impact on organizational absorptive capacity was established within our research. This is why it is important for practitioners (IT managers and executives) to understand that investment into a high-quality BI&A system is a necessary but not at all a sufficient condition to ensure organizational benefits (Ransbotham et al., 2016). Instead, they should pay attention to the nature of use considering it as a very important determinant of the BI&A use and reconcile the nature of the use with the intended organizational benefits.

Second, the mediation role of the BI&A use supports the notion that managers should carefully opt for both high system quality and information quality of the installed BI&A systems. High information quality raises trust in BI&A and prevents managers from reverting to intuitive decision-making and the underuse of BI&A (Erevelles, Fukawa, & Swayne, 2016; Matzler et al., 2007). Accordingly, the system quality of the selected BI&A solution should be high, so that organizations can cope with the increased amounts of data and information they are faced with in their everyday operations (Kiron & Shockley, 2011). Hence, the BI&A systems should be reliable, fast-responding, real-time systems that adapt easily to the organizational employees' needs, even the less-skilled ones. Nonetheless, despite the excitement about the possibilities that BI&A has to offer, firms should also be aware that delivering organizational benefits represents a challenging and time-consuming process.

5.3 Limitations and future research

Several limitations of this study are worth noting. First, although we employed multiple measures of the BI&A use, including the frequency, extent, and nature of use, they were all nevertheless self-reported. Self-reported usage may induce biases in the participants' perception on the actual usage, resulting in differences regarding either the underestimation or overestimation of use. However, since the research was done at an organizational level, and different organizations have different BI&A systems, measuring the actual usage of BI&A would be very difficult, as it would be hard to apply the same proxies for the degree of use. Yet, we welcome the measurement of the actual use in future research across organizations using the same or similar BI&A systems, for which proxies for the actual use can be applied.

Next, since a single-respondent research design was used, we consciously risked common method variance biases. Nevertheless, several remedies were taken to reduce such problems. First, we addressed the CMV during the procedural stage by not informing the respondents about what we were measuring and by separating the measurement of the predictor from those of the criterion variables. The latter was done by introducing in between new items that were not used in this study, with the purpose of achieving a psychological separation. In this step of the research, respondent anonymity was properly ensured. Second, we addressed the CMV bias in the statistical stage by using Harman's, marker variable analyses, and the full collinearity assessment approach. The results in this second step suggested no serious CMV in our study.

The sampling strategy applied in the paper included a sampling of the impact of the BI&A use on organizational benefits during the same time period. Hence, a longitudinal, sequential design with resampling can serve as a good starting point for more insights into the causality between the BI&A use and the process of creating organizational benefits, as well as shed more light on how this process changes over time. The strong theoretical foundations of the hypothesized relationships do provide confidence about the directions of the identified associations.

Nevertheless, this paper also shows that a large-sample analysis of the BI&A use at multiple levels is called for to examine the BI&A's successes in detail, for greater generalization across firms, industries, and countries. In addition, future research may draw on other theories, such as the resource-based view, dynamic capabilities perspective, and information processing view, with the aim of exploring the effects of other factors.

APPENDIX A

Table 4. *Measurement scales and items*

Items	Literature
<p><i>Degree of use</i></p> <p>Please indicate the extent to which you are currently using the BI&A. (EXT)</p> <p>Please indicate how often does your organization use BI&A. (FRQ)</p>	<p>Venkatesh, Brown, Maruping, and Bala (2008)</p>
<p><i>Nature of use</i></p> <p>My firm has clear rules for formatting or categorizing process knowledge. (TI1)*</p> <p>My firm uses Business Intelligence and Analytics technology that allows...</p> <p>...it to monitor its competition and business partners. (TI2)</p> <p>... employees to collaborate with other persons inside the organization. (TI3)*</p> <p>... people in multiple locations to learn as a group from a single source or at a single point in time. (TI4)</p> <p>... people in multiple locations to learn as a group from multiple sources or at multiple points in time. (TI5)*</p> <p>... it to search for new knowledge. (TI6)</p> <p>... it to map the location of specific types of knowledge. (TI7)</p> <p>... it to retrieve and use knowledge about its products and processes. (TI8)</p> <p>... it to retrieve and use knowledge about its markets and competition. (TI9)</p> <p>... generate and store new knowledge about its customers, partners, employees, or suppliers. (TI10)</p>	<p>Gold, Malhotra, and Segars (2001)</p>
<p><i>Acquisition (ASQ)</i></p> <p>The search for relevant information concerning our industry is an every-day business in our firm. (ASQ1)</p> <p>Our management motivates the employees to use information sources within our industry. (ASQ2)</p>	<p>Flatten, Engelen, Zahra, and Brettel (2011)</p>

Items	Literature
<p>Our management expects that the employees deal with information beyond our industry. (ASQ3)</p>	
<i>Assimilation (ASS)</i>	
<p>In our firm ideas and concepts are communicated cross-departmental. (ASS1)</p>	
<p>Our management emphasizes cross-departmental support to solve problems. (ASS2)</p>	
<p>In our company, there is a quick information flow, e.g., if a business unit obtains the important information it communicates this information promptly to all other business units or departments. (ASS3)</p>	
<p>Our management demands periodic cross-departmental meetings to interchange new developments, problems, and achievements. (ASS4)</p>	
<i>Transformation (TRF)</i>	
<p>Our employees have the ability to structure and use collected knowledge. (TRF1)</p>	
<p>Our employees are used to absorb new knowledge as well as to prepare it for further purposes and to make it available. (TRF2)</p>	
<p>Our employees successfully link existing knowledge with new insights. (TRF3)</p>	
<p>Our employees are able to apply new knowledge in their practical work. (TRF4)</p>	
<i>Exploitation (EXP)</i>	
<p>Our management supports the development of prototypes. (EXP1)</p>	
<p>Our firm regularly reconsiders technologies and adapts them accordant to new knowledge. (EXP2)</p>	
<p>Our company has the ability to work more effective by adopting new technologies. (EXP3)</p>	
<i>Information quality (INFQ)</i>	<p>Nelson, Todd, and Wixom (2005); B. H. Wixom and Watson (2001)</p>
<p>BI&A produces comprehensive information. (INFQ1)</p>	

Items	Literature
The information provided by BI&A is well formatted and clearly presented. (INFQ2)	
The information provided by BI&A is accurate. (INFQ3)	
BI&A provides me with the most recent information. (INFQ4)	
<i>System quality (SYSQ)</i>	Nelson, Todd, and Wixom (2005); B. H. Wixom and Watson (2001)
BI&A operates and performs reliably. (SYSQ1)	
BI&A makes information easy to access. (SYSQ2)	
BI&A can flexibly adjust to new demands or conditions. (SYSQ3)	
BI&A effectively integrates data from different areas of the company. (SYSQ4)	
It takes too long for BI&A to respond to requests. (SYSQ5) **	
<i>Marker variable (MARKER)</i>	Birkinshaw, Hood, & Jonsson (1998); Jaworski & Kohli (1993); Dill (1958); Volberda & Van Bruggen (1997)
Competition in our local market is intense. (C1)	
Price competition is a hallmark of our local market. (C4)	
Our clients regularly ask for new products and services. (D2)	
In a year, nothing has changed in our market. (D4) **	
Notes: *items eliminated due to low loading; **reverse scale item	

APPENDIX B

Table 5. *Loadings and cross-loading for the reflective measurement model*

Construct		Item	ASQ	ASS	TRF	EXP	DEGUSE	NATUSE
Absorptive capacity	Acquisition	ASQ1	0.731	0.273	0.401	0.198	0.205	0.283
		ASQ2	0.775	0.369	0.491	0.323	0.245	0.334
		ASQ3	0.734	0.331	0.322	0.325	0.056	0.274
	Assimilation	ASS1	0.361	0.863	0.430	0.486	0.309	0.320
		ASS2	0.318	0.761	0.315	0.346	0.115	0.165
		ASS3	0.234	0.694	0.375	0.237	0.188	0.295
		ASS4	0.433	0.811	0.560	0.387	0.350	0.409
	Transformation	TRF1	0.440	0.450	0.823	0.223	0.325	0.456
		TRF2	0.433	0.475	0.827	0.178	0.284	0.498
		TRF3	0.473	0.401	0.847	0.180	0.120	0.415
		TRF4	0.463	0.473	0.811	0.417	0.261	0.357
	Exploitation	EXP1	0.259	0.371	0.227	0.856	0.179	0.098
		EXP2	0.432	0.356	0.304	0.842	0.144	0.207
EXP3		0.256	0.464	0.234	0.815	0.441	0.155	
Degree of use	EXT	0.243	0.324	0.287	0.282	0.944	0.389	
	FRQ	0.198	0.285	0.284	0.293	0.957	0.431	
Nature of use	TI2	0.344	0.398	0.482	0.267	0.265	0.762	
	TI4	0.238	0.303	0.217	0.150	0.502	0.691	
	TI6	0.267	0.222	0.407	0.163	0.397	0.803	
	TI7	0.367	0.317	0.442	0.085	0.247	0.742	
	TI8	0.310	0.259	0.448	0.105	0.379	0.793	
	TI9	0.343	0.292	0.429	0.117	0.272	0.796	
	TI10	0.263	0.265	0.350	0.080	0.175	0.714	

Table 6. *Internal consistency, convergent validity, and discriminant validity for reflective constructs*

Latent construct	Composite reliability	AVE	Fornell-Lacker criterion																	
			ACAP	ASQ	ASS	TRF	EXP	DEGUSE	NATUSE	INFQ	SYSQ									
Absorptive capacity (ACAP)	0.848	0.584	0.764																	
Acquisition (ASQ)	0.791	0.558	0.729 ^a	0.747																
Assimilation (ASS)	0.864	0.616	0.828 ^a	0.438	0.785															
Transformation (TRF)	0.897	0.684	0.832 ^a	0.547	0.545	0.827														
Exploitation (EXP)	0.876	0.702	0.654 ^a	0.381	0.474	0.306	0.838													
Degree of use (DEGUSE)	0.950	0.904	0.380	0.231	0.319	0.300	0.303	0.951												
Nature of use (NATUSE)	0.904	0.575	0.506	0.400	0.387	0.520	0.185	0.433	0.758											
Information quality (INFQ)	^b	^b	0.346	0.209	0.327	0.261	0.249	0.624	0.529	^b										
System quality (SYSQ)	^b	^b	0.356	0.250	0.315	0.281	0.233	0.568	0.500	0.604	^b									

Note: Square roots of AVE on the diagonal (in bold font) and correlations among the latent constructs on the off-diagonal positions

^a Lower-order component of the higher-order construct of absorptive capacity

^b Not reported for formative constructs

Table 7. Discriminant validity assessment using the heterotrait-monotrait ratio (HTMT) criterion

	ASQ	ASS	TRF	EXP	DEGUSE	NATUSE	ACAP
Acquisition (ASQ)	0.615 [0.342;0.849]						
Assimilation (ASS)	0.754 [0.575;0.903]	0.654 [0.378;0.825]					
Transformation (TRF)	0.539 [0.301;0.801]	0.589 [0.354;0.755]	0.367 [0.171;0.612]				
Exploitation (EXP)	0.308 [0.093;0.545]	0.367 [0.145;0.608]	0.344 [0.118;0.578]	0.362 [0.180;0.584]			
Degree of use (DEGUSE)	0.548 [0.321;0.721]	0.457 [0.240;0.638]	0.609 [0.415;0.715]	0.216 [0.106;0.356]	0.475 [0.280;0.637]		
Nature of use (NATUSE)	1.009 [0.889;1.183]	0.986 [0.916;1.051]	0.942 [0.860;0.992]	0.814 [0.706;0.915]	0.426 [0.207;0.649]	0.569 [0.383;0.693]	
Absorptive capacity (ACAP)							

Note: The values in the brackets represent the 95% bias-corrected and accelerated confidence interval of the HTMT values obtained by running the bootstrapping routine with 5,000 samples in SmartPLS.

Table 8. Comparison of the baseline model and the model with the marker variable

Path	Baseline model			Model with marker MARKER		
	Est.	S.E	Sig.	Est.	S.E	Sig.
BIA_USE → ACAP	0.568	0.079	0.000	0.543	0.098	0.000
INFQ → DEGUSE	0.443	0.090	0.000	0.441	0.093	0.000
INFQ → NATUSE	0.351	0.111	0.002	0.347	0.113	0.002
SYSQ → DEGUSE	0.299	0.106	0.005	0.294	0.115	0.010
SYSQ → NATUSE	0.287	0.115	0.012	0.270	0.125	0.032
MARKER → ACAP				0.088	0.126	0.488
MARKER → DEGUSE				0.017	0.108	0.875
MARKER → NATUSE				0.055	0.111	0.625

Table 9. Standardized outer weights for formative measure items

Construct	Items	Outer Weights	t-value	95% BCa Confidence Interval	Outer Loadings	VIF
Information quality (INFQ)	INFQ1	0.598**	4.239	[0.754;0.974]	0.874**	1.489
	INFQ2	0.095	0.710	[0.341;0.823]	0.604**	1.474
	INFQ3	0.017	0.089	[0.087;0.879]	0.525*	1.364
	INFQ4	0.495**	3.199	[0.662;0.937]	0.832**	1.687
System quality (SYSQ)	SYSQ1	0.541**	3.394	[0.665;0.954]	0.851**	1.453
	SYSQ2	0.387**	3.453	[0.478;0.871]	0.665**	1.154
	SYSQ3	0.147	1.039	[0.142;0.766]	0.448**	1.144
	SYSQ4	0.165	1.207	[0.411;0.795]	0.614**	1.357
	SYSQ5	0.232	1.781	[0.219;0.732]	0.495**	1.112

Note: *Significant at .05 level; **Significant at .01 level

Table 10. Weights of the first-order constructs on the second-order construct

2nd Order Construct	1st Order Constructs	Weight	t-value
Business intelligence and analytics use (BIA_USE)	Degree of use (DEGUSE)	0.364	1.501
	Nature of use (NATUSE)***	0.781	4.096

Note: ***Significant at .001 level based on 5,000 bootstraps.

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