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Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective

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ABSTRACT

To survive in a dynamic and hyper-competitive business environment, firms are compelled to simultaneously introduce incremental and radical innovations. While it is recognised that business intelligence and analytics (BI&A) can support innovation and provide organisational value, the literature provides a limited understanding of its impact on balancing different innovation activities and ensuring performance gains. In this study, we examine the relationship between BI &A use, innovation ambidexterity, and firm performance by relying on the process theory of IS value creation as well as the dynamic capabilities perspective. We test our model using data collected from medium- and large-sized firms in Slovenia, applying partial least squares modelling. The results support the notion that BI&A use is positively associated with successful balancing between explorative and exploitative innovation activities, which in turn enhances firm performance. Our results also indicate that innovation ambidexterity is enhanced in two ways: indirectly through interaction with the firm's absorptive capacity, and directly by increasing the possibilities of faster experimentation with offerings of products or services and improved predictability of the value of new products or services.

Introduction

Firms today encounter greater competition and dynamism in the marketplace due to globalisation and ongoing technological developments. Maintaining an edge over the competition requires firms to innovate in two ways at once: incrementally and radically (Lin et al., 2013). Faced with the ever growing volume of data, firms are increasingly turning to business intelligence and analytics (BI &A) for useful insights, patterns and correlations that might facilitate efficient decision-making and increase economic value (Gartner, 2016). In this sense, BI&A refer to a variety of techniques, technologies, systems and applications aimed at helping a given organisation analyse diverse business and market data and information in a way that enhances its ability to make business decisions (Chen et al., 2012). Moreover, it enables a meaningfully broad knowledge search that integrates diverse external knowledge available to the firm, thereby providing new, potential alternatives for solving problems (Katila and Ahuja, 2002; Kowalczyk and Buxmann, 2015). Accordingly, prior literature describes BI&A as a strategic initiative that amplifies innovation capacity and business effectiveness (Lavalle et al., 2011; Watson and Wixom, 2007).

Although the manifest potential of BI&A has led to justifiably steady enthusiasm across the business world, most organisations that adopted BI&A report difficulties in attaining the anticipated competitive advantage, largely due to their failure to act on the insights provided to them (Barton and Court, 2012; Ransbotham et al., 2016). Many organisations are also disillusioned with over-promoted technological opportunities and unaware that the context through which the value of the provided insights and information

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has been unlocked is itself significant (Power, 2014). On the other hand, existing research is scarce and ultimately inconclusive, providing little by way of a theoretical framework or empirical evidence to validate the soundness or the legitimacy of transforming the insights and information provided by BI&A into operationally stronger innovation abilities. Most previous research seems mired in the facile attribution of a link between BI&A use and innovation suggesting that innovation is the result of a simple increase in the variety and volume of available information and insights (e.g., Brown et al., 2011; Kiron et al., 2012; Lavalle et al., 2011; Roberts and Piller, 2016). While these studies lend general support for the importance of BI&A for strengthening innovation abilities, many authors have recently called for further examination of this value-creation process since not every firm exposed to the same variety and volume of information and insights succeeds in capitalising on it via enhanced innovation (Duan et al., 2018; Erevelles et al., 2016; Foss et al., 2011).

Although many authors have found new external knowledge, from a narrow range of external sources facilitates exploitative innovation, and new external knowledge, from a broad range of external sources enhances explorative innovation (Chiang and Hung, 2010; Darroch, 2005; Jansen et al., 2006; Limaj and Bernroider, 2017), simply acquiring new information and knowledge does not intrinsically lead to innovation and improved performance (Lane et al., 2006). Instead, firms must be able to assimilate, transform and exploit this new knowledge to promote new or improved products and services (Chen et al., 2009). Along the same lines, Gao et al. (2017) and Duan et al. (2018) recently suggested that knowledge-creation abilities might underlie innovation processes due to BI&A use, and called for further consideration of this overlooked perspective. Extending this discourse, we seek to address this gap by drawing on the process theory of IT value creation and the dynamic capabilities perspective to pursue the following objectives: (i) to develop and validate a model to understand the role of BI&A use in balancing explorative and exploitative innovation activities and fostering firm performance; and (ii) to define the role of organisational absorptive capacity in the process of converting BI&A use into BI&A impacts.

This line of enquiry will provide several contributions to the IS and management literature. First, whereas existing research work has mainly theoretically examined the relationship between BI&A use and different innovation activities, we empirically specify the role of BI&A use in balancing between exploitative and explorative innovation activities, answering calls for research on the specific role of BI&A use in creating organisational value (Trieu, 2017; Wamba et al., 2015). Second, by introducing absorptive capacity as a mediation mechanism to the BI&A use -innovation ambidexterity relationship, we enhance comprehension of the interplay of lower-order technological capabilities with higher-order dynamic capabilities for securing organisational benefits, something many authors have suggested needs further exploration (Côrte-Real et al., 2017; Roberts et al., 2016; Sharma et al., 2014). Taken together, our theoretical model and empirical results offer a holistic understanding of the relationship between BI&A use, innovation ambidexterity, and firm performance.

The rest of the paper is structured as follows. First, we provide a literature review of the key concepts and theoretical foundations. Next, we present the development of the research model. We then explain the research methodology, while describing the data collection process and the measurement of the constructs. Following this, we present the data analysis and results. We conclude the paper by discussing the theoretical contributions and practical implications of the research while setting out the limitations and future research suggestions.

Theoretical background and research model

Business intelligence and analytics use

Ever since they first appeared in the mid-1950s, business intelligence systems have developed as large, structured data systems, typically in the form of data warehouses that allow various kinds of operations like reporting, real-time analysis, ad hoc query answering, and dashboards. Business intelligence was mainly used by decision-makers to improve the quality of the decision-making process (Negash and Gray, 2008). However, the large streams of data in different formats generated through high-velocity communication technologies, referred to as "big data", led to one of the biggest technological disruptions in the field of business intelligence (Agarwal and Dhar, 2014). This, in turn, spurred the emergence of BI&A which had the ultimate aim of facilitating knowledge acquisition and generation to support decision-making (Holsapple et al., 2014). Although different definitions of BI&A appear in the literature, we understand BI&A as referring to the technologies, techniques, systems, processes and applications used to acquire, store, analyse and transform business and market data and information into relevant knowledge for use in making better business decisions (Chen et al., 2012; Davenport et al., 2012; Wixom and Watson, 2012). Hence, BI&A relies on advanced analytic techniques such as data and text mining, forecasting, visualisation, machine learning, network analysis, neural networks, and graph analysis to gain business insights into the competition, market, products and processes (Holsapple et al., 2014).

Earlier studies showed that investments in BI&A are a necessary but an insufficient condition for value creation and the realisation of benefits (Hannula and Pirttimaki, 2003; Ransbotham et al., 2016; Yeoh and Popovič, 2016). Past IS research on business value creation enabled a complex yet inconsistent understanding of how the value of IS is created which saw IS researchers call for more research into how IS assets interact with complementary capabilities to co-create organisational benefits (Abbasi et al., 2016; Schryen, 2013). Some authors argued that a better understanding of the business value of IS can only emerge by exploring value-creation processes within a specific IS technological context (Elbashir et al., 2013; Fink et al., 2017; Trieu, 2017). Understanding the ways in which organisational benefits from BI&A use are delivered requires the integration of what is known about IT value creation while considering the unique features of BI&A. Our model relies on Trieu's (2017) adaptation of the process model of IT business value (Melville et al., 2004; Soh and Markus, 1995), with the main focus on use and competitive processes. BI&A assets can be converted into value by being embedded in products and services, improved decision-making, and streamlined business processes, which in turn contribute generated value to the firm (Ravichandran and Lertwongsatien, 2005). Greater BI&A use capabilities are only likely to create value when deployed to create unique complementarities with other firm capabilities (Powell and Dent-Micallef, 1997; Sangari and Razmi, 2015; Thamir and Poulis, 2015; Wamba et al., 2017). The value is expected to rise when capabilities are deployed in a mutually reinforcing manner (Henderson and Venkatraman, 1993). Firms which successfully bundle complementary organisational capabilities are likely to realise greater value as it is difficult for competitors to establish similar complementarity (Teece, 2007).

Relying on Bhatt and Grover's (2005) IT capabilities typology along with the conceptualisation of Wamba et al. (2017), we define organisational BI&A use as a lower-order dynamic capability that organisations can leverage to create leading-edge knowledge in a dynamic environmental setting. BI&A allows organisations to establish knowledge-creation routines as essential dynamic capabilities and to process considerable amounts of information via the information-processing capability, thereby facilitating the creation of knowledge (Chen et al., 2015; Olszak, 2014; Shollo and Galliers, 2016). Moreover, BI&A use demonstrates two important characteristics of dynamic capabilities: commonalities in the key features and idiosyncrasy in the details (Eisenhardt and Martin, 2000; Wang and Ahmed, 2007). Thus, as different firms develop effective knowledge-creation processes, this development moves along unique paths from different starting points. Firms deploy BI&A to suit their needs, starting from different points and following dissimilar development and deployment paths. Yet this is not a sufficient condition for the resource inimitability and immobility needed to sustain competitive advantage (Barney, 1991). Path-dependent, unique and idiosyncratic processes are the crux and source of competitive advantage (Teece et al., 1997; Wang and Ahmed, 2007). Firms must therefore embed their use of BI&A with other capabilities that are idiosyncratic to their firms, like absorptive capacity and innovation capability (Easterby-Smith and Prieto, 2008; Wang and Ahmed, 2007). We therefore apply the idea developed by Collis (1994), Danneels (2002) and Winter (2003) of referring to higher-order or meta-capability as a dynamic capability related to the learning-to-learn capability, which enables innovation and is self-renewing by creating lower-order capabilities.

Innovation ambidexterity

In the literature, innovation ambidexterity refers to finding a balance between exploitative and explorative innovation activities so as to introduce incremental and radical innovation for a superior sustainable performance (Benner and Tushman, 2003; Gibson and Birkinshaw, 2004; He and Wong, 2004; Jansen et al., 2006). Exploitative innovations are incremental improvements to existing products serving current customers and markets, while exploratory innovations are radical changes contained in new products which are introduced to serve new customers and markets (Benner and Tushman, 2003; He and Wong, 2004). Exploitative innovation refines products and increases efficiency, while exploratory innovation experiments with new features and is related to flexibility (Jansen et al., 2008). They both relate to new knowledge acquisition, although of different types and to different degrees (Gupta et al., 2006).

Despite the appeal of striking a balance between innovation activities, this objective poses a challenge because the activities are distinct and have different demands in terms of variability, timing and resources (March, 1991). This is especially the case for firms that have limited internal resources and poor access to external resources (Simsek, 2009); such firms are more likely to struggle to find a balance between these innovation activities. Ambidexterity may be seen as a midpoint on a continuum between both activities (March, 1991). Firms unburdened by limited internal or external resources can afford to make extensive forays into both activities (Cao et al., 2009; Simsek, 2009). However, firms that fail to simultaneously engage in high levels of both activities risk becoming mediocre in both (Atuahene-Gima, 2005; Ghemawat and Ricart Costa, 1993). When exploration is the dominant activity, failures of explorative innovations and extensive searches will lead to a 'failure trap', whereby firms fail before obtaining returns from experimentation with different products and services (Levinthal and March, 1993). By contrast, when exploitation is the dominant activity, short-run success increases the risk of stagnation, leaving firms unprepared for environmental changes (Gibson and Birkinshaw, 2004): firms get caught in a 'success trap' in which core capabilities become core rigidities (Leonard-Barton, 1995; Levinthal and March, 1993).

Therefore, we employ the orthogonality view that sees both activities as independent imperatives (Gupta et al., 2006). We conceptualise innovation ambidexterity as an organisational dynamic capability which encompasses the routines and processes that ambidextrous organisations rely on to allocate, mobilise, coordinate and integrate various contradictory innovative efforts (Jansen et al., 2009; O'Reilly and Tushman, 2008; Sirmon et al., 2007; Teece, 2007). Innovation ambidexterity is a complex dynamic capability that facilitates new capabilities and resource configurations and is associated with additional sources of sustained competitive advantage: advantage well beyond that given by each innovation activity separately (Smith et al., 2005; Winter, 2003). Innovation ambidexterity has been characterised as the firm's "learning-to-learn" ability which can be managed to promote the sensing and seizing of new opportunities and mitigate possible effects of path-dependence (O'Reilly and Tushman, 2008, 2013). Considering the complexity and pace of change organisations face as well as the time needed to adapt to new market requirements, internal alignment and the orchestration of a dual structure are needed (O'Reilly and Tushman, 2008). We agree with the way Jansen et al. (2009) describe balancing structural differentiation, in which exploratory and exploitative subunits are separated, with the subsequent need for integration for value generation. This allows for the coexistence of contradictory activities and prevents exploratory units from suffering from the dominant inertia (Andriopoulos and Lewis, 2009; Benner and Tushman, 2015; Jansen et al., 2009).

Absorptive capacity

Cohen and Levinthal (1990, p. 128) conceptualised 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 allows firms to better evaluate stimuli from the external environment by identifying new, external knowledge for assimilation and integration with prior, internally-related knowledge (Cohen and Levinthal, 1990; Kogut and Zander, 1992; Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009). Yet it is important for the firm to continuously invest in developing its absorptive capacity since it might eventually become unaware of new technological opportunities (Kogut and Zander, 1992; Lucas and Goh, 2009). Firms with high levels of absorptive capacity typically proactively exploit their technologies and market opportunities independent of their current performance, while a reactive response to external market opportunities is typical of firms with modest absorptive capacity (Lavie and Rosenkopf, 2006; Rothaermel and Alexandre, 2009).

Different conceptualisations of the absorptive capacity construct may be found in the literature (Jansen et al., 2005; Todorova and Durisin, 2007; Zahra and George, 2002). Absorptive capacity is frequently conceptualised as the level of relevant related knowledge already possessed by the firm. From this perspective, absorptive capacity is as an asset that is equal in value to the firm's existing knowledge base, operationalised with variables like R&D intensity and patents (Ahuja and Katila, 2001; Meeus et al., 2001; Tsai, 2001). This conception becomes problematic by failing to distinguish between prior related knowledge and absorptive capacity. Scholars argue that having prior related knowledge is a necessary but insufficient condition for absorptive capacity (Lane et al., 2006; Roberts et al., 2012; Van Den Bosch et al., 1999).

In this study, we rely on absorptive capacity as conceptualised by Zahra and George (2002) and Flatten et al. (2011), namely, as a dynamic capability that refers to knowledge creation and utilisation. In this view, absorptive capacity can be divided into four underpinning capabilities: knowledge acquisition, knowledge assimilation, knowledge transformation, and knowledge exploitation. Knowledge acquisition refers to an organisation's ability to identify and acquire information from external sources (Cohen and Levinthal, 1990; Zahra and George, 2002); knowledge assimilation is the ability of a firm to analyse and understand the information it acquires (Flatten et al., 2011); knowledge transformation relates to the combinative abilities and routines used to synthesise and apply the newly acquired knowledge and the existing knowledge from the prior knowledge base, and how this knowledge is internalised (Zahra and George, 2002); while knowledge exploitation is the application and utilisation of the knowledge so transformed to create new products, processes and routines (Flatten et al., 2011). Together these capabilities generate synergistic outcomes that enable a firm to achieve a competitive advantage by successfully exploiting new knowledge and engaging in new product innovation.

Research model and hypotheses

Our proposed research model presented in Fig. 1 shows the hypothesised relationships between BI&A use, innovation ambidexterity, and firm performance. The fundamental idea of the model is that the firm's ability to integrate different first-order and second-order dynamic capabilities in a reinforcing manner leads to performance gains. This value-creation process draws on the dominant IT value-creation theoretical mechanism that integrates different capabilities that generate business value (Kohli and Grover, 2008; Melville et al., 2004; Schryen, 2013). Since understanding of the value-creation process in the BI&A context requires a consideration of the unique features of the technological context, our model is theoretically grounded on Trieu's (2017) adaptation of the well-established process model of IT business value in the BI&A context. Specifically, we focused on two processes: (i) "BI&A use process" and (ii) "competitive process". Hence, in line with Soh and Markus (1995) discussion of process theory and the dynamic capabilities perspective (Easterby-Smith and Prieto, 2008; Eisenhardt and Martin, 2000; Teece, 2007), we posit that investments in BI &A are insufficient to realise value from technology; BI&A assets should instead be leveraged by BI&A use capability and integrated with other higher-order dynamic capabilities (absorptive capacity for knowledge creation and innovation ambidexterity) to generate organisational performance gains. Accordingly, we developed our hypotheses to explain the ways in which BI&A use is converted into BI&A impacts and organisational performance, as discussed in greater depth below.

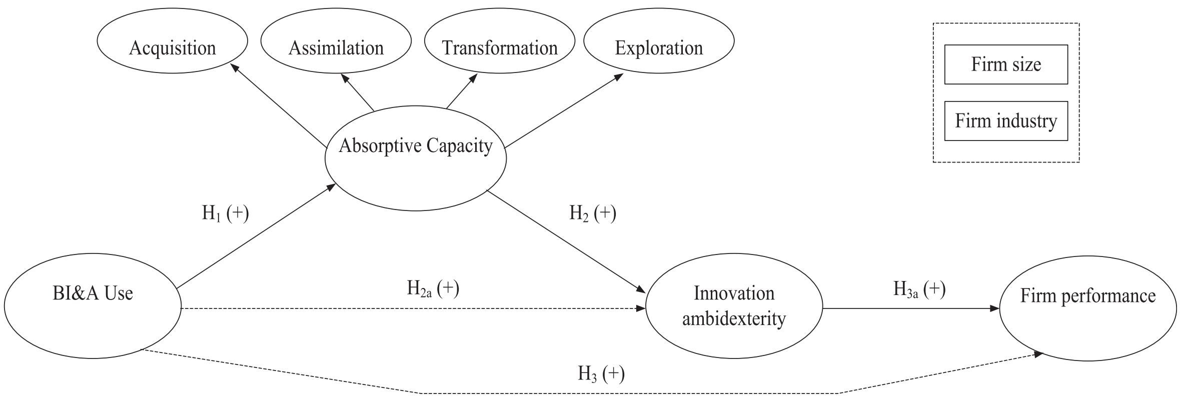

Fig. 1. Proposed conceptual model. Note: The dotted lines represent the hypotheses on mediation (indirect) effects via absorptive capacity and innovation ambidexterity.

Business intelligence, absorptive capacity, and innovation ambidexterity

Many firms face an information overload due to the ever-increasing amounts of data that are being generated. Both humans and organisations have limited knowledge and information-processing capacity, prompting firms to develop information filters (March, 1978; Sammut and Sartawi, 2012; Simsek, 2009). Over-searching negatively influences firm performance since organisations have difficulty managing the enormous number of ideas (Wales et al., 2013). Unsurprisingly, organisations are increasingly relying on BI&A to expand their absorptive capacity via increased information acquisition and processing ability (Elbashir et al., 2011; Srivardhana and Pawlowski, 2007).

Lower information processing costs allow BI&A to assume the role of active gatekeeper integrating insights and intelligence from a variety of sources for more holistic market intelligence (Altman et al., 2014; Fan et al., 2015). Thus, BI&A enable firms to facilitate the acquisition, storage and exchange of knowledge, as well as to integrate and store fragmented knowledge about the business environment and competition (Chuang, 2004; Gold et al., 2001; Lee and Choi, 2003). The processes of external knowledge acquisition and assimilation allow the firm to track market changes more effectively, further supporting the development and deployment of needed capabilities (Zahra and George, 2002). Therefore, we propose:

H_1: BI&A use positively relates to a firm's absorptive capacity for knowledge creation.

BI&A enable a broad knowledge search expanding the external knowledge available to the firm, thus providing new, possible alternatives for solving problems (Katila and Ahuja, 2002). This is, however, not a sufficient prerequisite for securing innovation because it is also important for firms to use their other capabilities to leverage external information and knowledge to support their innovation ability and increase their performance (Foss et al., 2011). The presence of valuable external information and insight does not automatically imply the successful harnessing of knowledge; instead, the external knowledge provided by BI&A enhances the existing knowledge base, which in turn promotes the advancement and generation of new products and services (Cohen and Levinthal, 1990; Gupta et al., 2006; Lichtenthaler, 2009; Nambisan, 2013; Roberts et al., 2016).

Cohen and Levinthal (1990) asserted that the ability to determine the value of new, external knowledge and information depends on the prior knowledge base, which reflects the fact that not all firms exposed to the same external knowledge derive equal innovation (Fabrizio, 2009; Forés and Camisón, 2016). The complementarity of the existing knowledge base with external sources of information and knowledge is a prerequisite for sustaining the innovation ambidexterity. As Rivkin (2001) point out, mature knowledge from a rich prior knowledge base, combined with diverse external knowledge, can create radical innovations that are difficult to imitate. Incremental improvements and refinements are more likely when the new, external knowledge is not fully understood and integrated, allowing less rapid adaptation to state-of-the-art market trends and customer tastes (Zhou and Li, 2012). Absorptive capacity creates synergy between the internal knowledge base and new external knowledge (Teece, 2007), enabling both incremental and radical innovation to take place. However, if the internal and external knowledge strongly overlap, this could limit the opportunities to generate new knowledge due to the path-dependent nature of absorptive capacity (Lord and Ranft, 2000). Moreover, if the internal knowledge becomes very specialised, it might impede the assimilation of external knowledge by virtue of the "Not-Invented-Here" syndrome (Cohen and Levinthal, 1990). There must be a strong prior knowledge base together with openness to new external knowledge.

Firms must rely on a combination of internal and external knowledge sources to maintain a high-level effort in both explorative and exploitative innovation activities since a lack of exploration will lead to an underdeveloped knowledge base that cannot be exploited while a lack of exploitation will lead to lower absorptive capacity and a reduced ability to support exploration (Smith and Lewis, 2011). Firms with higher absorptive capacity levels are better equipped to predict future technological innovation and avoid overreliance on individual innovation processes (either exploratory or exploitative) (Lin and Chang, 2015). As some earlier literature suggests, absorptive capacity and innovative ambidexterity are closely related organisational dynamic variables that firms must integrate and reconfigure to achieve congruence with the constantly changing environment (O'Reilly and Tushman, 2008; Rosenkopf and Nerkar, 2001; Teece, 2007) in order to sustain a competitive advantage (Lane et al., 2006; Zahra and George, 2002). Absorptive capacity supported by BI&A allows real-time information and improved cross-functional communication among the individuals included in the process, building intuition about the changing marketplace that then allows for faster organisational adaptation (cf., Eisenhardt and Martin, 2000; O'Reilly and Tushman, 2008). Moreover, it increases the frequency and magnitude of knowledge acquisition and strengthens the learning orientation required to support innovation activities (Hult et al., 2004). At the same time, innovation ambidexterity as a higher-order, learning-to-learn capability that facilitates the alignment, development and renewal of lower-order capabilities and is an outcome of organisational learning (Danneels, 2002; Winter, 2003). Hence, learning processes are the dominant source and a common characteristic of dynamic capabilities (Zahra et al., 2006). In addition, innovation ambidexterity integrates and configures dispersed and contradictory innovation efforts across differentiated exploratory and exploitative structural units (Gupta et al., 2006; Jansen et al., 2009; O'Reilly and Tushman, 2008), preventing firms from becoming mediocre in both (Atuahene-Gima, 2005). We therefore propose the following hypotheses:

H_2: A firm's absorptive capacity for knowledge creation positively relates to its innovation ambidexterity.
H_{2a}: The absorptive capacity for knowledge creation positively mediates the relationship between BI&A use and innovation ambidexterity.

Business intelligence, innovation ambidexterity, and firm performance

Research into the performance gains stemming from BI&A use reports mixed results. Namely, some scholars argue that investments in BI&A are a necessary but not a sufficient condition for improved firm performance (Akter et al., 2016; Ransbotham et al., 2016; Shuradze and Wagner, 2016; Wamba et al., 2017), while others identify a positive link between BI&A use and firm performance (Gupta and George, 2016; Wang and Hajli, 2017). The absence of a reliable positive link between BI&A investments and firm performance may be explained by various factors, such as failure to consider the indirect benefits of BI&A use, environmental factors, and the influence of time lags (Chae et al., 2014; Sharma et al., 2014). Although BI&A enables a broad knowledge search, expanding the external knowledge available to the firm and thereby providing new potential alternatives for solving problems (Katila and Ahuja, 2002), new external information and knowledge do not necessarily yield benefits (Lane et al., 2006). Process theory posits that organisations can achieve improved organisational performance through the conversion process of the creation of an "intermediate outcome" such as new products or development of new services (Soh and Markus, 1995; Trieu, 2017). Firms can only expect an increased performance when BI&A use is deployed to create unique complementarities with other dynamic capabilities, such as through the support of innovation abilities (Duan and Cao, 2015; Foss et al., 2011; Lavalle et al., 2011; Ravichandran and Lertwongsatien, 2005; Wamba et al., 2017). Therefore, we propose the following hypothesis:

H_3: A firm's innovation ambidexterity mediates the relationship between the firm's BI&A use and firm performance.

Firms continuously introduce new technological innovations in their products and services to stay competitive and satisfy changing customer demands (Benner and Tushman, 2002; Hill and Rothaermel, 2003; Jansen et al., 2006). Yet the main goal of innovation is to achieve and maintain a satisfactory organisational performance (Damanpour et al., 2009). Innovation activities are, however, highly uncertain, which accounts for the inconsistent empirical findings on the relationship between different innovation activities and firm performance (Camisón and Villar-López, 2014; Darroch, 2005; Hitt et al., 1997; Morgan and Berthon, 2008). Despite the controversy found in the literature, the prevailing research evidence suggests there is a positive association between innovation and firm performance. For instance, in their research on technological innovation in manufacturing firms He and Wong (2004) report that exploitative innovation and explorative innovation significantly affect firm performance, as measured by sales growth. In a similar vein, Jansen et al. (2006) determine that innovation ambidexterity, under different environmental conditions, positively influences profitability-based indexes of firm performance. Nonetheless, when conducting a qualitative case study Andriopoulos and Lewis (2010) found that the ability to manage paradoxical innovation tension simultaneously ultimately exerted a positive influence on firm performance.

Different theoretical arguments may be found in support of the beneficial role of innovation for firm performance. A high level of innovation permits the firm to assume 'first-mover' advantages, increase its responsiveness to changing customer demands and preferences, thereby preventing firms from "lock-out" effects (Leonard-Barton, 1995; Siggelkow and Rivkin, 2006) and competency traps (Levitt and March, 1988). Further, innovating firms tend to be more sensitive to opportunities in the external environment, proactively exploiting new technologies (Hill and Rothaermel, 2003). Such heightened responsiveness and proactiveness allow firms to introduce new products or services containing improved or advanced features that lead to a better firm performance in terms of revenue, profit and a market-share increase. Continuous investment in innovation can also trigger consecutive innovation via the generation of dynamic capabilities for improved firm performance (Ghemawat and Ricart Costa, 1993; Teece et al., 1997). Hence, following research by Tushman and O'Reilly (1996) and Benner and Tushman (2003), we argue that dynamic capabilities are rooted in the simultaneous introduction of exploitative and explorative innovation, and not their rhythmic pacing (oscillation between periods of exploration and exploitation) (Brown and Eisenhardt, 1998) because competence development is a lengthy process and environmental change is continuous. Moreover, the coexistence of both contradictory activities prevents exploratory units from dominant managerial inertia present in the mainstream innovation activities (Andriopoulos and Lewis, 2009; Benner and Tushman, 2015; Jansen et al., 2009). The coordination and integration of exploratory and exploitative innovation efforts in a new, value enhancing way creates a difficult-to-imitate advantage (Helfat and Peteraf, 2009). Therefore, we posit:

H_{3a}: A firm's innovation ambidexterity positively relates to firm performance.

Research methodology

Sampling, data collection, and sample properties

The survey instrument relied on a comprehensive literature review whereby all constructs were operationalised by validated measurement scales found in the literature. To secure content validity, we asked five IS experts and related management researchers to review and assess the survey's content, scope and purpose (Lawshe, 1975; Lynn, 1986) and accordingly refined several items to simplify interpretation and ensure that the items properly tap into the study's specific context. The questionnaire was developed and disseminated in the English language to ensure identical meaning across different language groups. We drew our participants from internal mailing lists of the Strategic Research Innovation Partnership (SRIP) MOBILITY ACS + and the Purchasing Association of Slovenia, together with a public database containing details of the 101 most successful Slovenian firms in 2016. The total initial sample invited to participate in the web-based survey was 500.

To guarantee the quality of the data, we applied three screening criteria, namely, the respondent: (1) had deep knowledge of the

Table 1
Sample demographics.

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	38.2
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

organisation's management; (2) had over 3 years' experience in BI&A initiatives; and (3) held a management, executive or IT position in the firm. The sample comprised employees from primarily medium and large organisations, according to the current EU guidelines (European Commission, 2005). Regarding the respondents' positions, IT and business executives were almost equally represented. The sample's demographic characteristics are shown in Table 1.

In total, 97 responses obtained after two rounds of the survey were usable, indicating an overall response rate of 19.4%. Three responses were removed due to straight-lining. A mean value replacement was applied to handle missing data as the amount of missing data per indicator did not exceed 5% (Hair et al., 2017a). We also examined the skewness and kurtosis of the data distribution and found that most of the data for each indicator were normally distributed. We conducted a wave analysis to assess any non-response bias between early- and late-responding groups (Armstrong and Overton, 1977). Our analysis showed no significant differences (5% significance level, $p > .05$) between the early- and late-responding groups regarding organisational attributes such as firm size (χ^2 test, p=2.255) and return on investment (χ^2 test, p=.427); thus, we found no evidence of response bias. Nevertheless, we took different remedies to prevent potential common-method-variance (CMV) issues. During the procedural stage, we did not inform the respondents about what we were measuring and introduced new items to achieve psychological temporal separation. During the statistical stage, we assessed potential CMV using three approaches: Harman's ex-post single-factor analysis, the full collinearity assessment approach, and Rönkkö and Ylitalo's (2011) six-step marker variable approach (Kock, 2015; Podsakoff et al., 2003; Rönkkö and Ylitalo, 2011). Relying on exploratory factor analysis, we found that no single factor accounted for most of the covariance among the measures, with the first factor extracted accounting for 35.743% of the variance. Further, the full collinearity assessment (Kock, 2015) showed all factor-level VIF values were within the range between 1.274 and 2.429, that is, below the recommended threshold of 3.3. (Diamantopoulos and Siguaw, 2006). When applying Rönkkö and Ylitalo's (2011) six-step marker variable approach we found no differences of note between the baseline and the model with the marker variable, while all paths saw no change in the level of statistical significance (Table F-1 in Appendix F). Therefore, common method variance appeared unlikely to threaten the validity of the present study.

Structural equation modelling approach

We relied on variance-based partial least squares (PLS-SEM) to estimate the structural equation model (Chin, 1998; Hair et al., 2017a; Lohmoller, 1988). PLS-SEM is especially useful when a model includes second-order variables and complex mediation relationships (Hair et al., 2012; Ringle et al., 2012). Moreover, PLS-SEM has proven useful while analysing relatively small sample sizes in medium- and high-complexity model setups (Reinartz et al., 2009). Pursuant to recommendations made in earlier studies (Hair et al., 2017b; Ringle et al., 2012), we checked the sample size's suitability using power analysis. Assuming the frequently-used level of statistical power of 80%, and the maximum number of arrows pointing at a construct (in our case, four), we needed at least 41 (or 53 according to *G*Power* analysis) data sets to detect R^2 values of at least 0.25 (with a 5% probability of error). Although relatively small, the acquired datasets fulfil the sample size requirements and were thus used to assess the proposed model with Smart PLS 3 software (Ringle et al., 2015).

Measurement and validation of the constructs

Independent variables

Business intelligence and analytics use. We measured BI&A use with ten items adapted from Gold et al. (2001). Following criticism expressed in earlier literature regarding the inappropriateness of frequency and duration of use to capture the value of BI&A use for knowledge creation (Burton-Jones and Straub Jr., 2006; Grublješič and Jaklič, 2014; Petter et al., 2013), we instead selected nature of use, which rendered BI&A use a proxy variable for the benefits of its use (Gold et al., 2001; Seddon, 1997; Shollo and Galliers, 2016). We aimed to measure whether BI&A support firms in monitoring consumers, the market and the competition; in tracking internal and external knowledge flows; in pursuing, generating and storing knowledge; and in retrieving and using the knowledge so gathered. All items were measured using a 7-point scale, ranging from 1 ("*strongly disagree*") to 7 ("*strongly agree*").

Absorptive capacity. We measured a firm's absorptive capacity with a measurement scale developed and tested by Flatten et al. (2011). Hence, absorptive capacity is modelled as a second-order hierarchical latent variable with four first-order components: knowledge acquisition, assimilation, transformation, and exploitation. The response scale ranged from 1 ("*strongly disagree*") to 7 ("*strongly agree*").

Dependent variables

Innovation ambidexterity. Following prior studies (Gibson and Birkinshaw, 2004; He and Wong, 2004; Jansen et al., 2016), we used the two-step approach to develop a customised measure for innovation ambidexterity. Since innovation ambidexterity involves achieving a balance between exploitative and exploratory innovation activities, we first measured exploitative innovation and explorative innovation with two six-item scales from Jansen et al. (2006). We assessed and provided evidence of the constructs' reliability, as well as their convergent and discriminant validity (Table D-1 and Table E-1). To construct the measure for ambidexterity as a combined measure of exploratory and exploitative innovation, we followed earlier works (Jansen et al., 2009; Lubatkin et al., 2006; Raisch et al., 2009) and ran four regression analyses, with performance as the dependent variable. The unconstrained model treats both exploitative and exploratory innovation as separate independent variables. On the other hand, the three constrained regression equations combined the two measures into a single index by summing, subtracting or multiplying (Junni et al., 2013). After running an *F*-test to compare the three models, we found the additive model was superior to the other two approaches without any significant loss of information relative to the unconstrained model. Therefore, we measured ambidexterity by adding exploitative and exploratory innovation, and considered them as orthogonal and thus complementary activities, and not ends of a continuum (Cao et al., 2009).

Firm performance. Many research studies have analysed the impact of innovation ambidexterity on firm performance (Atuahene-Gima, 2005; Jansen et al., 2006). These studies used different measures to measure firm performance, including return on investment (Jansen et al., 2005), average profitability (Jansen et al., 2006), return on sales, return on assets (He and Wong, 2004; Kostopoulos et al., 2011) or a combination of revenues, profits and market growth (Cao et al., 2009; Lin et al., 2013). As one-dimensional indicators of firm performance are strongly discouraged due to their tendency to produce biased estimations (Raisch and Birkinshaw, 2008), we used a broader set of indicators to capture firm performance. Specifically, the perceptual performance information consisted of seven items that required respondents to rate their firm's performance relative to their main competitors in the previous 3 years on a 5-point Likert scale, in terms of return on investment, return on sales, profit growth, return on assets, sales growth, market share growth, and the firm's overall reputation (Cao et al., 2009; Li and Atuahene-Gima, 2001; Lubatkin et al., 2006; McDougall et al., 1994). In addition, we used secondary archival data to triangulate the perceptual performance information. Using publicly available objective performance information taken from the AMADEUS and Bisnode databases, we created a subsample of firms ($n = 11$) and analysed the correlation between the archival-based and perceptual performance information. We used sales growth and return on assets (ROA) as objective performance information because it is the most frequently relied on in the literature (He and Wong, 2004; Junni et al., 2013; Lin et al., 2007; Rothaermel and Alexandre, 2009). Since the performance effects of exploration are more time-distant than the immediate performance effects of exploitation (Uotila et al., 2009), we tried to attenuate the lags and annual fluctuations of objective data by collecting data for the three years between 2014 and 2017. Following prior research (Ireland et al., 2002; Rothaermel and Alexandre, 2009), we averaged the sales growth and ROA information over this period and ran non-parametric correlation analyses. We found the survey-based performance indicators of this subsample were significantly correlated with the archival-based performance indicators (ROA ($r = 0.657$, $p = 0.028$), sales growth ($r = 0.809$, $p = 0.003$)), confirming the high correlation of the two measurement approaches.

Control variables

We included additional control variables to control for possible confounding explanations, specifically firm size and industry sector. ***Firm size*** (number of full-time employees) is often associated with inertia and difficulty related to information processing that affects firm adaptation and growth (He and Wong, 2004; Tushman et al., 1985). Further, firm size can impact innovative ambidexterity (Andriopoulos and Lewis, 2009; Uotila et al., 2009). For instance, Cao et al. (2009) found that small firms which, by being relatively resource-constrained can benefit more from achieving a balance between exploration and exploitation, while firms with greater access to internal and external resources can benefit more from simultaneously combining high levels of both exploration and exploitation. Likewise, Lee, Wu and Liu (2013) found that large firms are more capable of simultaneously engaging in exploratory and exploitative innovation by way of structural divisibility. Here, firm size is a dummy variable that takes a value of 1 for micro firms, 2 for small firms, 3 for medium firms, and 4 for large firms.

Further, the ***industry sector*** is associated with disparities in firm adaptation and performance (He and Wong, 2004; Lubatkin et al., 2006). Tambe (2014) also identified diversity in industry sectors' investment in BI&A. Therefore, we controlled two broad industry sectors of manufacturing and service by including an industry dummy variable (1 = manufacturing, 0 = service) in the model to explicitly control for unobserved industry idiosyncrasies (Table B1).

Results

Measurement model

We modelled all constructs included in the analysis as reflective constructs. Following Flatten et al. (2011), we modelled the absorptive capacity construct as a reflective-reflective second-order construct, with four first-order constructs: acquisition (ACQ), assimilation (ASS), transformation (TRF), and exploitation (EXP). We then applied the repeated indicator approach on the higher-order (Mode A) construct, as recommended by Becker, Klein, and Wetzels (2012). The measurement items for all constructs are included in the Table A-1 (Appendix A).

Reflective measurement

We initially focused on evaluating the construct measures' reliability and validity through tests for indicator reliability, construct reliability, convergent validity and discriminant validity (Gefen and Straub, 2005; Ringle et al., 2012). We removed two items based on an assessment of the indicator reliability (TI1 and EXPL6), resulting in increased average variance extracted. As Table C-1 reveals, all indicators reached satisfactory indicator reliability with outer loadings exceeding 0.70 and with one indicator exhibiting a slightly lower loading of 0.668. Moreover, the reflective measurement models achieved a composite reliability of 0.836 or higher, suggesting the reliable internal consistency of the construct measures. Next, we used average variance extracted (AVE) and found all values exceeded the threshold value of 0.5 (Fornell and Larcker, 1981; Henseler et al., 2009). For the second-order ACAP construct, we manually calculated AVE and composite reliability following the Hair et al. (2017a) guidelines (Table D-1).

Further, we examined the constructs' discriminant validity using two measures – the criteria developed by Fornell and Larcker (1981) and the indicators' cross-loadings (Chin, 1998) – and found the constructs show satisfactory discriminant validity. In addition, by using the heterotrait-monotrait ratio (HTMT) criterion, we found that all values were below the conservative threshold value of 0.85 (Hair et al., 2017a), reconfirming the established discriminant validity (Table E-1). However, discriminant validity between the higher- and lower-order absorptive capacity constructs cannot be established, which is expected due to the use of the repeated indicators approach. Based on these findings, we concluded that the presented reflective construct measures are valid and reliable.

Structural model

To evaluate the structural model, we provided a collinearity assessment, the squared multiple correlations R^2, structural path coefficients, the predictive relevance of endogenous variables using Stone Geisser's Q^2 values, effect size values f^2, and the effect size values q^2 as recommended by Hair et al. (2017a). We used the path-weighting scheme and a stop criterion set at 10^{-7}, with 5,000 iterations of resampling and the no-sign-change option as settings in the PLS SEM algorithm in SmartPLS 3. First, we examined the collinearity among endogenous and corresponding exogenous constructs and found all VIF values were below the recommended threshold of 3.3 (the highest VIF among the explanatory variables was 1.556). Further effect size values f^2 showed that small to moderate effects were present, while the Q^2 values for all reflective endogenous constructs were above zero, supporting the predictive relevance of the endogenous latent variables. We also calculated the relative impact of predictive relevance and found small and moderate effects. Table 2 presents the results of the hypothesised relationships, *t*-values, standard errors, and effect sizes, while Fig. 2 displays the path coefficients, R^2 and Q^2.

The results show that the conceptual model explains 55.5% of the variation in innovation ambidexterity and 20.5% of the variation in firm performance. Hence, BI&A use is statistically significant in explaining absorptive capacity ($\beta = 0.598, p < .01$) and absorptive capacity is statistically significant in explaining innovation ambidexterity ($\beta = 0.616, p < .01$). Hypotheses H_1 and H_2 are thus supported. Moreover, the results indicate innovation ambidexterity is significantly and positively related to firm performance, supporting hypothesis H_3. However, we did not find a significant influence of the control variables such as industry type (industrial vs. service) and firm size on firm performance.

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
BI&A USE → ACAP	0.598**	0.556	N/A	0.078	7.650	[0.405; 0.718]	H_1 supported
ACAP → IA	0.616**	0.548	0.515	0.083	7.379	[0.442; 0.770]	H_2 supported
IA → FP	0.464**	0.183	0.074	0.139	3.346	[0.179; 0.715]	H_{3a} supported
FIRM SIZE → FP	0.132	0.021	0.008	0.091	1.453	[-0.069; 0.296]	Not supported
FIRM INDUSTRY → FP	0.018	0.000	0.002	0.106	0.172	[-0.194; 0.219]	Not supported

Note: *Significant at the 0.05 level.
** Significant at the 0.01 level.

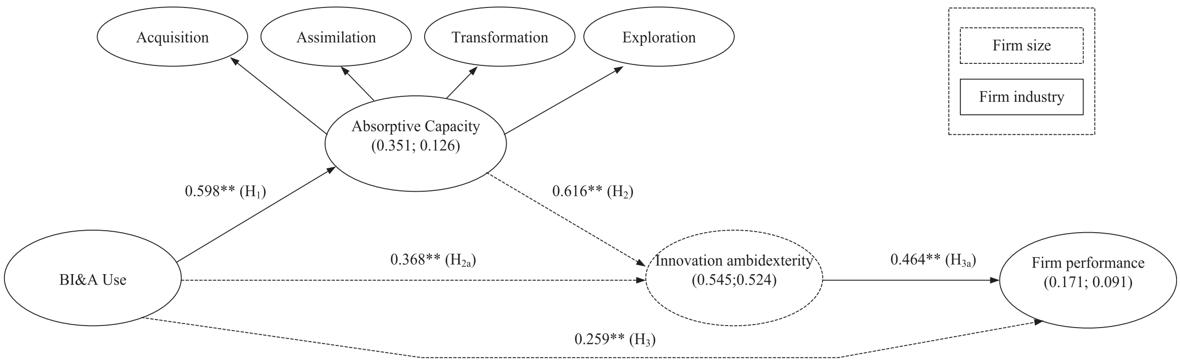

Fig. 2. Estimated model. Notes: *Significant at the 0.05 level; **Significant at the 0.01 level; (R^2 adjusted, Q^2) given for endogenous constructs. The dotted lines represent the mediation hypotheses (indirect effects) via absorptive capacity and innovation ambidexterity.

Mediation analysis

We hypothesised that absorptive capacity would mediate the relationship between BI&A use and innovation ambidexterity and that innovation ambidexterity would mediate between BI&A use and firm performance. To test for mediation, we conducted the bootstrapping test (Hair et al., 2017a). We found both indirect effects were significant since neither of the 95% confidence intervals included the value of zero. Yet, the result shows that absorptive capacity partially (complementarily) mediates between BI&A use and innovation ambidexterity as both the direct and indirect effects are significant and point in the same direction, giving partial support for H_{2a}. At the same time, innovation ambidexterity was found to fully mediate between BI&A use and firm performance, and the direct effect was found to be non-significant ($t = 0.470$; $p = .638$), supporting H_3 (see Table 3).

Discussion and conclusion

Existing research gives anecdotal, conceptual and empirical evidence to back up the strong assertions made about the ability of BI&A to enhance firms' innovation ability and firm performance (Lavalle et al., 2011; Stubbs, 2014). This study aimed to further understand the mechanisms by which BI&A contributes to innovation ambidexterity and firm performance from a use perspective. Based on prior research on innovation, we proposed and tested a research model that integrated the domains of dynamic capabilities, knowledge management, and information processing. The key findings suggest that BI&A use is positively associated with the ability to balance competing innovation activities, which in turn enhances the firm's performance. This association was mainly explained through the firm's absorptive capacity, which enables firms to leverage external information and their knowledge-supporting innovation ability.

Theoretical contributions

This study offers several theoretical contributions to the BI&A and IS literature. First, the study integrates insights gained from applying the process theory of IT value creation (Soh and Markus, 1995; Trieu, 2017) and the dynamic capabilities perspective to explain how BI&A use is associated with innovation ambidexterity and firm performance. Although a few models for BI&A value creation have recently appeared in the IS literature (Božič and Dimovski, 2019; Chen et al., 2015; Côrte-Real et al., 2017; Fink et al., 2017; Trieu, 2017; Vidgen et al., 2017) more research is needed into the role of BI&A in organisational learning, knowledge management, and information processing in order to achieve a holistic understanding of the role played by BI&A in balancing innovation activities and fostering firm performance (Duan et al., 2018; Sharma et al., 2014). Our study makes progress towards this goal by focusing on the processes involved in converting BI&A use into BI&A impacts, and then into organisational performance gains. By concentrating primarily on knowledge creation and the enhancement of innovation abilities we are able to better understand the process of converting BI&A use into organisational value.

Our research suggests that BI&A use enhances innovation ambidexterity mainly through the knowledge-harnessing that is enabled by organisational absorptive capacity. This is in line with recent anecdotal evidence (Duan et al., 2018); yet, instead of focusing on

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
BI&A USE → IA	0.189*	[0.016; 0.356]	2.174	0.368**	[0.223; 0.517]	4.895	H_{2a} partially
BI&A USE → FP	−0.062	[−0.313; 0.196]	0.470	0.259**	[0.098; 0.450]	2.842	H_3 supported

Note:
* Significant at the 0.05 level.
** Significant at the 0.01 level.

environmental scanning, we explain the mechanism of translating useful external information and insights as a result of BI&A use into the generation of innovative products and services via the underlying processes of knowledge acquisition, assimilation, transformation and exploitation. At times there is the simplistic belief that an increased volume and variety of information will automatically lead to stronger innovation abilities, however, we found support for one of the key tenets of absorptive capacity theory, namely, that firms are likely to derive innovation from external insights and knowledge once they hold the ability to recognise its value (Cohen and Levinthal, 1990). Moreover, by modelling absorptive capacity as a mediation mechanism in the BI&A use - innovation ambidexterity relationship, our study sheds light on the underexplored association between BI&A and absorptive capacity, answering previous calls in the IS literature for its further investigation (e.g., Gao et al., 2017; Roberts et al., 2012). Our study focuses on the interplay of BI&A use, absorptive capacity, and innovation ambidexterity as complementary capabilities and assets that together create business value (via radical and incremental innovation) which, in turn, leads to economic performance.

We also found a significant direct association between BI&A use and innovation ambidexterity. Although significantly smaller than the indirect effect occurring through absorptive capacity, it appears that BI&A use directly influences a firm's innovation ability. One possible explanation was offered by Zhan, Tan, Ji, Chung and Tseng's (2017) research; they found that BI&A use directly influences innovation abilities by shortening the feedback process between the rounds of production and consumption, identifying weaknesses in products or services earlier in the development phase, and supporting responsive product development. Other examples in the literature of BI&A use influencing a firm's responsiveness support these findings. For instance, Google matches ads to content in real time using algorithms that have identified trends and relationships (Lycett, 2013), and Netflix analyses masses of real-time streaming data to help decide which pilot projects will be most successful in the future (Xu et al., 2016). Thus, while earlier authors noted that firms might be better equipped to innovate as a result of BI&A use (Kowalczyk and Buxmann, 2015; Manyika et al., 2011), our study makes an original contribution by explaining that innovation abilities are enhanced in two ways: (i) by the increased diversity and richness of the information and knowledge available through interaction with the firm's absorptive capacity (determining unmet customer needs and underserved market segments); and (ii) by increasing the possibilities for experimentation and predictability of the value of new products and services, early in the planning process. This study therefore provides a holistic understanding of the role played by BI&A use in balancing explorative and exploitative innovation activities, thereby enriching existing literature that explores the BI&A value-creation process (e.g., Fink et al., 2017; Trieu, 2017). Departing from the conventional resource based conceptualisations of value creation that fail to explain the BI&A value-creation process in dynamic environments (Mikalef and Pateli, 2017), our study emphasises the importance of adopting a dynamic approach to deepen our understanding of firm performance variations.

Previous studies have indicated that BI&A use contributes directly to firm performance (e.g., Wamba et al. (2017) and Akter et al. (2016)). Our results indicate innovation ambidexterity to mediate this association. As discussed by Cao et al. (2015) and Foss et al. (2011), this may be attributed to the fact that BI&A use can only influence firm performance when deployed to create unique complementarities with other dynamic capabilities. Moreover, this agrees with Lonnqvist and Pirttimaki (2006) who state that BI&A value can only be created (and measured) through the process of using information/intelligence. Thus, instead of expecting a taken for granted improvement in firm performance because of investments in BI&A, firms need to figure out how to leverage BI&A to enhance their innovation abilities; it is this which ultimately brings improved performance. The coexistence of explorative and exploitative innovation activities will restrain any overreliance on a single innovation process, preventing firms from losing long-term competitive advantage by facilitating dynamic adaption to environmental changes. Our research found that the control variables of firm size and industry type, had no significant effect on firm performance; this is noteworthy since the findings in the literature seem contradictory and inconclusive (Lubatkin et al., 2006; Raisch et al., 2009).

Practical implications

Our study has important practical implications for managers who are engaged in BI&A implementation. As Ransbotham et al. (2016) noted, many organisations struggle to ascertain how to use the information and insights provided by BI&A, and firms which are successful in taking advantage of BI&A use are more the exception than the rule. Empirical evidence shows that practitioners must concentrate on enhancing the firm's BI&A-supported innovation abilities if they are to successfully translate BI&A use into improved firm performance. Given that available external data and information are abundant, firms should increasingly use BI&A to support absorptive capacity's underlying processes, thus mitigating the bounded rationality phenomenon (Knippenberg et al., 2015) and provide useful knowledge for innovation (Duan and Cao, 2015). Firms thus need to formulate tactics to stimulate the development of absorptive capacity (e.g. to build up employees' technological, human and relational skills, improve the information transfer by boundary-spanning individuals), which in turn create favourable settings for different innovation activities (Castro et al., 2013; Tsai, 2001).

Our study findings suggest that BI&A can be leveraged as a source of improved competitive advantage by supporting exploitative and exploratory innovation abilities. Firms need to proactively employ the knowledge gained from BI&A to both improve existing products and services and to develop new products and services that fundamentally depart from existing ones. Although striking a balance between these sometimes conflicting innovation activities is not easy, an imbalance here may produce competence traps that negatively impact long-term firm performance (Andriopoulos and Lewis, 2010). Thus, practitioners must simultaneously capitalise on the greater diversity and richness of the information and knowledge available; and explore ways to ensure greater adaptability with faster experimentation with the offerings (products or services) and improved predictability of the value of new products and services (with reduced variability of the causal factors and associations between them). Firms need to envision the organisational innovation landscape and make sure that its use of BI&A matches its requirements. Moreover, the insights provided by BI&A should be made available to everyone involved in the innovation process, along with a detailed description of the meaning and limits of the findings.

Senior executives must consider the time-lagged effects of different innovation activities on firm performance. Instead of optimising the short-term benefits of BI&A investments, senior executives should understand the strategic value of BI&A and ensure the necessary capabilities renewal that will lead to sustained competitive advantage, avoiding the tendency to reinforce exploitation of existing competencies over exploration of new ones (Gibbert, 2005; Wang et al., 2015; Yeow et al., 2018). Such a managerial agenda of capabilities renewal will over time provide economic returns that may further become a source of new innovation activities. Still, efforts must be made to provide managers with appropriate professional skills and knowledge of BI&A technologies (programming, computational, and statistical), which increases the awareness of the differences that arise from using different BI&A technologies (George et al., 2014).

Limitations and future research

Several limitations that may provide directions for future research are worth noting. First, our single-respondent research design might raise the issue of common method variance and unobserved heterogeneity, even though we took steps in the procedural and statistical stages to limit such issues. The statistical analyses we used provided evidence that common method variance is not a serious threat in his study. However, future research should design and administer the questionnaire using few *ex ante* approaches in the research design stage to prevent common method bias issues, such as collecting data from different sources of information for some of the variables.

Our sampling strategy included data collection at a single point in time, but we believe that a longitudinal, sequential design might provide more insights into the causality between BI&A use and firm performance and the underlying dynamic processes. Moreover, our empirical study considered perceptual performance measures over the past 3 years. Considering that financial benefits of exploration are usually more distant in time (He and Wong, 2004), future studies might benefit from collecting firm performance data that span a period longer than 3 years.

Other research opportunities are apparent. To assess the competitive process, we relied on the interaction of different dynamic capabilities that create strategic organisational value. Future research could expand our theorising by including operational business value measures (Melville et al., 2004) that focus on productivity enhancement and cost efficiency improvement. In addition, our model focuses on managing the paradoxes of exploitative and explorative product and service innovation. Future research could add important insights to the literature by testing the model in other areas of innovation like business process innovation while considering other value-creation measures, such as sustainability.

Another avenue for future work pertains to the specification of contingency variables that might affect the hypothesised relationship between BI&A use, innovation ambidexterity, and firm performance. Here, future studies should consider external contingency factors, like environmental dynamism and environmental competitiveness, that may introduce pressures opposing the innovation ambidexterity (Chang et al., 2011; Jansen et al., 2006), to improve our understanding of how BI&A use interacts with various internal and external factors to produce performance gains. Moreover, the consideration of organisational structure as a contingency variable may lead to valuable insights. This study looked at Slovenian firms of different sizes. Given the potential differences across countries in terms of financial resources for IT investments, the availability of a well-trained workforce, English language literacy etc., and their impact on BI&A use and innovation ability, future research should examine the presented associations across different cultural and social contexts, with special attention to emerging economies. Namely, context-specific variations as well as a larger sample encompassing different countries would enhance the generalisability of the results.

Conclusion

This research study provides theoretical and empirical evidence on the relationship between BI&A use, innovation ambidexterity, and firm performance. Relying on the process theory of IT value creation in the unique context of BI&A as well as the dynamic capabilities perspective, this study suggests that BI&A use is positively associated with innovation ambidexterity, which in turn creates organisational performance gains. The relationship between BI&A use and innovation ambidexterity is explained in two ways; by mediation of the firm's absorptive capacity, and by the greater possibilities for faster experimentation with offerings of products or services and improved predictability of the value of new products or services. The findings offer practical implications about the required interplay of different dynamic capabilities to gain strategic advantages from the use of BI&A.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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Appendix A

Table A1
Measurement scales and items.

Items	Literature
Nature of use (BI&A USE)	Gold et al. (2001)
My firm has clear rules for formatting or categorising process knowledge. (TI1)*	
My firm uses Business Intelligence and Analytics technology that allows…	
… it to monitor its competition and business partners. (TI2)	
… employees to collaborate with other persons inside the organisation. (TI3)	
… people in multiple locations to learn as a group from a single source or at a single point in time. (TI4)	
… people in multiple locations to learn as a group from multiple sources or at multiple points in time. (TI5)	
… it to search for new knowledge. (TI6)	
… it to map the location of specific types of knowledge. (TI7)	
… it to retrieve and use knowledge about its products and processes. (TI8)	
… it to retrieve and use knowledge about its markets and competition. (TI9)	
… generate and store new knowledge about its customers, partners, employees or suppliers. (TI10)	
Absorptive capacity (ACAP)	Flatten et al. (2011)
Acquisition (ASQ)	
The search for relevant information concerning our industry is an every-day business in our firm. (ASQ1)	
Our management motivates the employees to use information sources within our industry. (ASQ2)	
Our management expects that the employees deal with information beyond our industry. (ASQ3)	
Assimilation (ASS)	
In our firm, ideas and concepts are communicated cross-departmentally. (ASS1)	
Our management emphasises cross-departmental support to solve problems. (ASS2)	
In our company, there is a quick information flow, e.g. if a business unit obtains important information it communicates this information promptly to all other business units or departments. (ASS3)	
Our management demands periodic cross-departmental meetings to exchange new developments, problems and achievements. (ASS4)	
Transformation (TRF)	
Our employees have the ability to structure and use collected knowledge. (TRF1)	
Our employees are used to absorbing new knowledge, preparing it for further purposes and making it available. (TRF2)	
Our employees successfully link existing knowledge with new insights. (TRF3)	
Our employees are able to apply new knowledge in their practical work. (TRF4)	
Exploitation (EXP)	
Our management supports the development of prototypes. (EXP1)	
Our firm regularly reconsiders technologies and adapts them according to new knowledge. (EXP2)	
Our company has the ability to work more effectively by adopting new technologies. (EXP3)	
Innovation ambidexterity (IA)	Jansen et al. (2006)
Exploratory innovation (EXPR)	
Our unit accepts demands that go beyond existing products and services. (EXPR1)	
We invent new products and services. (EXPR2)	
We experiment with new products and services in our local market. (EXPR3)	
We commercialise products and services that are completely new to our unit. (EXPR4)	
We frequently utilise new opportunities in new markets. (EXPR5)	
Our unit regularly uses new distribution channels. (EXPR6)	
Exploitative innovation (EXPL)	
We frequently refine the provision of existing products and services. (EXPL1)	
We regularly implement small adaptations to existing products and services. (EXPL2)	
We introduce improved, but existing products and services to our local market. (EXPL3)	
We improve our efficiency in providing products and services. (EXPL4)	
We increase economies of scales in existing markets. (EXPL5)	
Our unit expands services for existing clients. (EXPL6)*	
Firm performance (FP)	Li and Atuahene-Gima (2001); McDougall et al. (1994)
Return on investment (FP1)	
Return on sales (FP2)	
Profit growth (FP3)	
Return on assets (FP4)	
Sales growth (FP5)	
Market share growth (FP6)	
Firm's overall reputation (FP7)	

(*continued on next page*)

Table A1 (*continued*)

Items	Literature
Marker variable (MARKER)	Birkinshaw et al. (1998); Jaworski and Kohli (1993); Dill (1958); Volberda and Van Bruggen (1997)
The 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 B1
Industry sector – control variable description.

Industry sectors (dummy)		Frequency	Percent (%)
Manufacturing	Agriculture, forestry, hunting	1	1.03
	Manufacturing	34	35.05
	Electricity, gas, water supply	8	8.25
	Construction	1	1.03
Total number of firms in manufacturing industries		44	
Services	Wholesale and retail trade	18	18.56
	Hotels and restaurants	1	1.03
	Transport, storage and communication	16	16.49
	Financial intermediation	4	4.12
	Real estate, renting and business activities	6	6.19
	Education	1	1.03
	Health and social work	1	1.03
	Other services industries	6	6.19
Total number of firms in service industries		53	

Appendix C

Table C1
Loadings and cross-loadings for the reflective constructs.

Construct		Item	ACQ	ASS	TRF	EXP	BI&A USE	EXPL	EXPR	FP
Absorptive capacity	Acquisition	ASQ1	**0.819**	0.379	0.478	0.245	0.361	0.425	0.373	0.132
		ASQ2	**0.797**	0.405	0.560	0.372	0.463	0.457	0.427	0.131
		ASQ3	**0.764**	0.375	0.352	0.283	0.319	0.325	0.419	0.209
	Assimilation	ASS1	0.370	**0.873**	0.476	0.526	0.361	0.325	0.499	0.325
		ASS2	0.395	**0.861**	0.467	0.435	0.353	0.321	0.501	0.326
		ASS3	0.351	**0.754**	0.465	0.337	0.432	0.448	0.521	0.423
		ASS4	0.485	**0.807**	0.579	0.400	0.495	0.454	0.532	0.215
	Transformation	TRF1	0.465	0.599	**0.866**	0.362	0.611	0.476	0.538	0.269
		TRF2	0.448	0.466	**0.838**	0.189	0.513	0.476	0.484	0.189
		TRF3	0.553	0.438	**0.833**	0.185	0.446	0.550	0.582	0.218
		TRF4	0.521	0.509	**0.817**	0.428	0.391	0.531	0.554	0.223
	Exploration	EXP1	0.328	0.437	0.271	**0.904**	0.189	0.184	0.417	0.298
		EXP2	0.397	0.435	0.367	**0.901**	0.249	0.310	0.485	0.312
		EXP3	0.254	0.473	0.274	**0.783**	0.196	0.119	0.260	0.266
Nature of use		TI2	0.415	0.441	0.498	0.309	**0.768**	0.500	0.462	0.200
		TI3	0.387	0.420	0.422	0.231	**0.748**	0.404	0.328	0.232
		TI4	0.318	0.470	0.382	0.267	**0.765**	0.382	0.302	0.214
		TI5	0.251	0.382	0.382	0.188	**0.755**	0.351	0.285	0.123
		TI6	0.297	0.262	0.454	0.173	**0.767**	0.359	0.306	0.105

(*continued on next page*)

Table C1 (*continued*)

Construct	Item	ACQ	ASS	TRF	EXP	BI&A USE	EXPL	EXPR	FP
	TI7	0.511	0.403	0.537	0.170	**0.834**	0.470	0.342	0.068
	TI8	0.425	0.414	0.562	0.164	**0.856**	0.478	0.438	0.180
	TI9	0.381	0.328	0.432	0.107	**0.764**	0.331	0.399	0.132
	TI10	0.353	0.313	0.380	0.074	**0.715**	0.370	0.381	0.122
Exploitative innovation	EXPL1	0.452	0.335	0.604	0.215	0.437	**0.792**	0.625	0.252
	EXPL2	0.415	0.394	0.405	0.277	0.463	**0.798**	0.536	0.281
	EXPL3	0.432	0.438	0.467	0.225	0.390	**0.847**	0.681	0.227
	EXPL4	0.472	0.452	0.569	0.143	0.494	**0.879**	0.634	0.276
	EXPL5	0.211	0.191	0.328	0.075	0.297	**0.668**	0.339	0.148
Explorative innovation	EXPR1	0.305	0.416	0.315	0.206	0.330	0.450	**0.702**	0.395
	EXPR2	0.335	0.429	0.344	0.331	0.274	0.553	**0.780**	0.410
	EXPR3	0.504	0.534	0.542	0.325	0.413	0.608	**0.862**	0.335
	EXPR4	0.398	0.545	0.544	0.389	0.436	0.603	**0.867**	0.373
	EXPR5	0.481	0.602	0.703	0.469	0.479	0.609	**0.854**	0.454
	EXPR6	0.417	0.447	0.572	0.423	0.310	0.642	**0.761**	0.446
Firm performance	FP1	0.089	0.324	0.257	0.332	0.058	0.214	0.358	**0.721**
	FP2	0.198	0.330	0.227	0.237	0.143	0.293	0.412	**0.750**
	FP3	0.130	0.234	0.139	0.288	0.132	0.222	0.328	**0.806**
	FP4	0.211	0.300	0.189	0.323	0.176	0.224	0.430	**0.767**
	FP5	0.117	0.239	0.149	0.212	0.073	0.215	0.382	**0.786**
	FP6	0.172	0.284	0.293	0.169	0.338	0.326	0.409	**0.733**
	FP7	0.096	0.329	0.170	0.238	0.136	0.098	0.305	**0.747**

Appendix D

Table D1
Internal consistency, convergent validity and discriminant validity for reflective constructs.

Latent construct	Composite reliability	AVE	Fornell-Lacker criterion								
			ACAP	ACQ	ASS	TRF	EXP	BI&A USE	EXPL	EXPR	FP
Absorptive capacity (ACAP) [a]	0.864	0.616	**0.763**								
Acquisition (ACQ)	0.836	0.630	0.753[b]	**0.794**							
Assimilation (ASS)	0.895	0.681	0.855[b]	0.487	**0.825**						
Transformation (TRF)	0.904	0.703	0.856[b]	0.592	0.604	**0.838**					
Exploration (EXP)	0.898	0.748	0.602[b]	0.512	0.467	0.354	**0.865**				
Nature of use (BI&A USE)	0.931	0.602	0.598	0.486	0.497	0.586	0.246	**0.776**			
Exploitative innovation (EXPL)	0.898	0.640	0.602	0.512	0.467	0.606	0.242	0.530	**0.800**		
Explorative innovation (EXPR)	0.917	0.651	0.723	0.512	0.621	0.644	0.454	0.470	0.721	**0.807**	
Firm performance (FP)	0.905	0.576	0.379	0.195	0.385	0.270	0.339	0.200	0.303	0.499	**0.759**

Notes: Square roots of AVE on the diagonal (in bold) and correlations among the latent constructs on the off-diagonal positions
[a]Second-order construct; [b]Lower-order component of the higher-order construct of absorptive capacity.

Appendix E

Table E1
Discriminant validity assessment using the heterotrait-monotrait ratio (HTMT) criterion.

	ACQ	ASS	TRF	EXP	BI&A USE	EXPL	EXPR	FP	ACAP
Acquisition (ACQ)									
Assimilation (ASS)	0.627 [0.349;0.846]								
Transformation (TRF)	0.749 [0.585;0.883]	0.704 [0.443;0.858]							
Exploration (EXP)	0.489 [0.253;0.720]	0.619 [0.398;0.785]	0.409 [0.194;0.649]						
Nature of use (BI&A USE)	0.586 [0.379;0.759]	0.560 [0.322;0.725]	0.652 [0.462;0.774]	0.276 [0.113;0.469]					
Exploitative innovation (EXPL)	0.630 [0.409;0.805]	0.535 [0.297;0.729]	0.692 [0.492;0.832]	0.276 [0.124;0.433]	0.579 [0.371;0.735]				
Explorative innovation (EXPR)	0.636 [0.431;0.821]	0.711 [0.508;0.853]	0.713 [0.531;0.838]	0.510 [0.320;0.663]	0.506 [0.315;0.674]	0.800 [0.636;0.907]			
Firm performance (FP)	0.246 [0.126;0.334]	0.453 [0.284;0.597]	0.307 [0.152;0.462]	0.397 [0.212;0.558]	0.226 [0.138;0.303]	0.337 [0.182;0.540]	0.558 [0.348;0.728]		
Absorptive capacity (ACAP)	0.945 [0.0.921;1.077]	0.978 [0.913;1.039]	0.945 [0.861;0.999]	0.802 [0.687;0.900]	0.638 [0.455;0.764]	0.654 [0.457;0.788]	0.788 [0.651;0.886]	0.432 [0.260;0.570]	

Note: The values in brackets represent the 95% bias-corrected and accelerated confidence interval of the HTMT values obtained by running the bootstrapping routine with 5000 samples in SmartPLS.

Appendix F

Table F1
Comparison of the baseline model and the model with the marker variable.

Path	Baseline model			Model with marker		
	Est.	S.E	Sig.	Est.	S.E	Sig.
BIA_USE → ACAP	0.598	0.078	0.000	0.569	0.088	0.000
ACAP → IA	0.616	0.083	0.000	0.601	0.097	0.000
IA → FP	0.464	0.139	0.001	0.468	0.136	0.001
MARKER → ACAP				0.117	0.130	0.370
MARKER → IA				0.088	0.100	0.383
MARKER → FP				−0.050	0.153	0.742

Appendix G. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsis.2019.101578.

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