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ORIGINAL ARTICLE

Building novel capabilities to enable business intelligence agility: results from a quantitative study

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Abstract The class of business intelligence (BI) systems is widely used to guide decisions in all kinds of organizations and across hierarchical levels and functions. Organizations have launched many initiatives to accomplish adequate and timely decision support as an important factor to achieve and sustain competitive advantage. Given today's turbulent environments it is increasingly challenging to bridge the gap between establishing a long-term strategy and quickly adopting to the dynamics in market competition. BI must address this field of tension as it was originally used to retrospectively reflect an organization's performance and build upon stability and efficiency. This study aims to understand and achieve an agile BI from a dynamic capability perspective. Therefore, we investigate how dynamic BI capabilities, i.e., adoption of assets, market understanding, and intimacy as well as business operations, impact the agility of BI. Starting from a literature review of dynamic capabilities in information systems and BI, we propose hypotheses to connect dynamic BI capabilities with the agility to provide information. The derived hypotheses were tested using partial least squares structural equation modeling on data collected in a questionnaire-based survey. The results show that the lens of dynamic capabilities provides useful means to foster BI agility. The study identifies that technological advancements like in-memory technology seem to be a technology enabler for BI agility. However, an adequate adoption and integration of BI assets as well as the focus on market orientation and business operations are crucial to reach BI agility.

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1 Introduction

Contemporary business environments require organizations to react quickly to changing market conditions. Likewise, a stable organizational backbone and branding is essential for keeping up a distinguishable long-term strategy to position itself in the market (Aghina et al. 2016). This area of conflict between stability and innovativeness emphasized with the increasing importance of digitization in organizations holds especially true for business intelligence (BI) as a distinct class of information systems (IS). BI supports managers and information workers in making better decisions based on data and information and is one of the top priorities of organizations (Foley and Guillemette 2010; Luftman et al. 2015). It summarizes technological tools, organizational structures, and procedural guidelines for data processing, reporting, and decision support systems (Watson 2009). To provide a stable, reliable, and robust infrastructure many organizations have implemented the concept of data warehouse (DWH)-based BI. It systematically extracts, harmonizes, and provides data to reflect the organization's single point of truth with the fundamental DWH principles of integration, subject-orientation, time-variance, and non-volatility (Inmon 1996; Rifaie et al. 2008; Watson and Wixom 2007b). Although many organizations have launched BI initiatives with the intention to implement or improve BI, there is evidence that a significant number of organizations have failed to realize the expected benefits of BI and that BI implementation projects are expensive, time-consuming, and risky undertakings (Wixom and Watson 2001, 2010; Chenoweth et al. 2006; Gartner 2009; Xu and Hwang 2007; Shin 2003). Moreover, BI is more and more challenged by dynamic business environments that require a flexible use and adaption of information provision. In addition to the established retrospective reporting and data analysis functionalities, growing amounts of unstructured or semi-structured data from numerous sources like social media, e-mail or sensor data have increased the demand for agile, future-oriented, and timely BI (Baars et al. 2014; Negash 2004; Baars and Kemper 2008).

Consequently, the challenge of rapid and frequent adaption is very present for BI and its common multi-layered architectures (Sambamurthy et al. 2003; Krawatzeck et al. 2015; Zimmer et al. 2012). While organizational agility has been popular in practice and academia for decades, agility in terms of BI is still in its early stage and is starting to gain attention (Baars and Hütter 2015; Krawatzeck et al. 2015; Moss 2009; Watson and Wixom 2007a; Zimmer et al. 2012). Current work addresses the goal of achieving BI agility with a catalog of actions (Krawatzeck and Dinter 2015), the identification and selection of measures (Baars and Hütter 2015) or with architectural and governance approaches (Zimmer et al. 2012). Attempts for achieving agility in the field of BI also take development approaches like Scrum (Schwaber 1997) or BI-adapted versions (Hughes 2008; Collier 2011) into account. These concepts were indeed introduced many years ago for BI and decision support, e.g. Sprague (1980) or Watson et al. (1984), and are without a doubt valuable, particularly for user-facing components of BI. Nevertheless, they look at the way in which BI systems are developed and not at the agility of the resulting system itself. Thus, methods focusing on the delivery cycle are criticized for not being sufficient to achieve agility in BI (Evelson 2011) or else its value is questioned in general as BI is data- and not code-centric (Moss 2007; Caruso 2011).

All of the existing attempts concentrate on "how" to achieve BI agility, but none investigate the drivers and effects on BI agility, i.e., the "what" (research gap 1). We understand BI agility in a broader sense, i.e., as the behavior that BI shows with regard to change, the readiness and the process of BI according to change, the architecture and infrastructure used for BI, the value that it creates for its customers and also if and how the business model of an organization is facilitated. Hence, there is still a lack of research in this area. Especially, as none of the available research analyzes the integration of BI into the external and internal processes of an organization, particularly in dynamic environments. In addition, none of the work known to the authors puts a special emphasis on in-memory (IM) technology to make BI more agile (research gap 2). IM technology is on the rise as an agility enabler, evoked by turbulent environments, growing competition among organizations, and the trend and ability of complex analytics as a basis for decision-making (MarketsandMarkets 2015). It has the potential to overcome the drawbacks of DWH-based BI on traditional disk-resident databases (DRDB) and the separation of transactional and dispositive systems (Plattner 2009; Schaffner et al. 2009). As a growing number of organizations are currently switching their BI applications from DRDB to in-memory databases (IMDB), we consider IM technology as highly relevant for our research (Bort 2015; MarketsandMarkets 2015; Gartner 2013).

In a time characterized by market dynamism and the need for BI as a timely, flexible, and agile capability, it is crucial for organizations to build and sustain the ability to adapt their decision-making capabilities. Dynamic capabilities are the ability of an organization to adapt or renew its resources to create an output of greater value, either to address changing environments and/or to change existing routines and thus the way an organization solves problems (Teece et al. 1997; Wade and Hulland 2004; Makadok 2001; Zahra et al. 2006). Hence, the concept of dynamic capabilities serves as a theoretical lens to build theory on achieving BI agility and to identify its antecedents. It provides the necessary theoretical means to understand the relation between BI capabilities and their impact on BI agility. Summarizing, this paper addresses the following research questions:

- How do dynamic capabilities in the domain of BI impact each other, and how can organizations use them to achieve BI agility as a basis for timely and viable decision support?
- Do emerging technologies like IMDB make a difference in achieving BI agility, either direct or via mediating effects?

The remainder of the paper is structured as follows. First, we provide a theoretical background for BI, IM-technology, and agility in the field of BI. Afterwards, we focus on dynamic capabilities. Thereafter, we introduce the connection between dynamic capabilities and BI based on a structured literature review. Next, we explain our research model and derive hypotheses based on the existing literature. After detailing the methodology and scale development we present the results of a quantitative study. We then discuss the results and show implications for managerial practice and research. We close this paper with an outlook of future research opportunities as well as study limitations.

2 Theoretical foundation and related work

2.1 Business intelligence and in-memory technology

This study understands BI as "a broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions" (Watson 2009). It is an umbrella term for systems and processes that turn raw data into useful information (Wixom and Watson 2010; Chen and Siau 2012). BI systems support decision-makers through business analyses on the basis of internal and external data (Chung et al. 2005; Watson and Wixom 2007b; Abbasi and Chen 2008). BI has been introduced to measure corporate performance based on IS data and also to support problem and opportunity identification, decision-making and the alignment of operations with the corporate strategy (March and Hevner 2007). It became popular in the 1990s and has evolved over time. Mostly structured data collected from different source systems characterizes this stage of BI 1.0 (Chen et al. 2012). With the rise of the Internet and Web in the early 2000s, new possibilities for acquiring and processing information from these sources emerged. They focus on semi-structured or unstructured data from the Web, Internet or social media (BI 2.0). As the number of mobile devices such as smartphones or tablets is strongly increasing, a new level of BI arises that deals with mobile analytics and sensor-based content, referred to as BI 3.0 (Chen et al. 2012).

The rising integration of external data sources such as social media and the resulting increase in unstructured data produced by the growing number of devices has become more and more important for BI in recent years (Davenport and Harris 2007; Laney 2001). This trend is accompanied by technological advancements like IMDB. In contrast to traditional storage solutions using DRDB, e.g., magnetic hard disks, an IMDB keeps its data permanently in the main memory. Due to recent price reductions in the hardware market and dedicated compression techniques, even the entire data of large-size organizations can be economically stored in-memory. Furthermore, huge performance gains, up to factor 1000 with praxis data (Plattner 2009), can be achieved.

Hence, IM technology may have the potential to drastically expand and improve BI. Taking DWH-based BI architectures as an example, IM technology allows for greater flexibility in architecture and data modeling and, moreover, enables new analytic scenarios and business use cases (Knabke et al. 2014). As current (DWH-based) BI architectures focus on reporting, integration, and stability (Caruso 2011; Inmon 1996), it is difficult to meet the requirements of future-oriented analytics. Here, the use of IMDB for BI and new architectural approaches offer enormous potential. IMDB will support the real-time analysis of operational processes and might overcome the traditional separation of transactional and dispositive systems and thus initiate a shift in organizations' IT and IS landscapes (Plattner 2009; Schaffner et al. 2009). This paradigm shift has the potential to change the way BI and the supply of information is currently done. It will not only affect BI and DWH architectures but also requires organizations to adopt their structures, infrastructure, processes, and staff accordingly.

2.2 The value of agility for BI

Agility drew mainstream attention in the business literature through the work of Goldman et al. (1991) with regard to agile manufacturing. It is considered crucial for business success and the term agility has been used in many domains and industries (Overby et al. 2006; Sharifi and Zhang 1999; Sambamurthy et al. 2003; Conboy 2009; Towill and Christopher 2002). Definitions of agility often have the ability to cope with unforeseen changes in common. Nevertheless, they are ambivalent in scientific literature and industry (van Oosterhout et al. 2006; McCoy and Plummer 2006). Only some have made attempts to derive a holistic definition of agility by conducting a cross-discipline literature review. For instance, Conboy and Fitzgerald define agility as "the continual readiness of an entity to rapidly or inherently, proactively or reactively, embrace change, through high quality, simplistic, economical components and relationships with its environment" (Conboy and Fitzgerald 2004).

In recent years, academia (e.g., Baars et al. 2014) and practice (e.g., Luftman et al. 2015) recognized the relevance for BIA. In a survey of key information technology and management issues "business agility" ranked number two for key management concerns and "analytics/BI" number two for "top application and technology investments" (Luftman et al. 2015). We draw on our previous work based on a structured literature review to understand agility in the field of BI (Knabke and Olbrich 2013). Figure 1 shows the identified dimensions of BI agility. Briefly summarized, change behavior is a central construct of agility and describes the behavior of BI with regard to change. A system can behave reactively or proactively, it can create or even learn from change. Perceived customer value (PCV) highlights the importance of quality, simplicity, and economy as being of value to the customer of BI. Change readiness

<table>
<tr><td colspan="3">Creation of change</td><td colspan="3">Proaction to change</td><td colspan="3">Reaction to change</td><td colspan="3">Learning from change</td><td>Change Behavior</td></tr>
<tr><td colspan="4">Economy</td><td colspan="4">Quality</td><td colspan="4">Simplicity</td><td>Perceived Customer Value</td></tr>
<tr><td colspan="4">Continuous</td><td colspan="4">Ad hoc / Spontaneous</td><td colspan="4">Planned</td><td>Change Readiness</td></tr>
<tr><td colspan="4">Sense</td><td colspan="4">Diagnose</td><td colspan="4">Respond</td><td>Change Processing</td></tr>
<tr><td colspan="3">Scalability</td><td colspan="3">Reusability</td><td colspan="3">Reconfigurability</td><td colspan="3">Architecture</td><td>Architecture & Infrastructure</td></tr>
<tr><td colspan="4">Support</td><td colspan="4">Improvement</td><td colspan="4">Enablement</td><td>Business Model</td></tr>
</table>

Fig. 1 Framework for BI agility (adapted from Knabke and Olbrich 2013)

describes the time frame or point in time at which BI is able to adapt to changing environments. It can either happen in a continuous process, planned or "ad-hoc." The actual physical length of time is dependent on the context of BI and may differ for a strategic, tactical, and operational BI. Change processing comprises the ability of the BI to sense, analyze, and respond to a change. Architecture & infrastructure incorporates the data model and architecture of BI. Agile BI may require a new architectural approach which is among others, reusable, reconfigurable, and scalable. Additionally, agile BI should support, improve or enable the business model, e.g., by supporting the business processes of an organization (Rouse 2007). As we focus on what impacts BI to become agile in this study, and not how BI is created, we excluded the approach, i.e., agile versus traditional methods, from the framework for understanding the BI agility depicted below. The BI environment is dynamic and BI has to cope with these dynamics to adapt to its environment. Thus, we understand environment, e.g., the industry of an organization, as one important reason for why BI agility has to be achieved and address it with the integration into the dynamic capabilities theory. Hence, BI is perceived as agile if it contributes to the dimensions of change behavior, perceived customer value, change absorption, change processing, data model & infrastructure, and business model.

Although organizations see BI as one of the top priorities and are heavily investing in it, many organizations fail to achieve value and thus to gain advantage from their BI investments (Gartner 2016; Olszak 2016; Luftman et al. 2015; Clavier et al. 2012; Wixom and Watson 2010). There is evidence, however, that BI plays an important role in driving competitive advantage and performance (as a successor of agility) with the capabilities it provides (Chen and Siau 2012). Dynamic capabilities have proved to be a valid concept in IS research to analyze IS/IT initiatives, its connected capabilities and their impact (Mikalef et al. 2016; Chen and Siau 2012; Sambamurthy et al. 2003). Hence, we believe the theory of dynamic capabilities is highly valuable in the field of BI, BI agility, and as a theoretical foundation of our research. Particularly if applied in turbulent business environments and/or to change existing capabilities to improve decision-making.

2.3 Dynamic capabilities as strategic management theory

The dynamic capabilities concept extended the theory of the resource-based view (RBV) of an organization (Wernerfelt 1984) by market perspective (Drnevich and Kriauciunas 2011). Taking an inside-out perspective, the RBV argues that an organization can achieve competitive advantage with the use and configuration of an organization's tangible and intangible resources (Barney 1991; Wernerfelt 1984; Wade and Hulland 2004). RBV has been criticized for only focusing on the core, internal resources and stable environments while not taking into account surrounding factors like rapidly changing environments. The theory of dynamic capabilities (Teece et al. 1997; Winter 2003; Helfat and Peteraf 2003; Eisenhardt and Martin 2000) aims to overcome this gap by complementing the RBV by strategic capability to adjust and (re-)configure its resources to dynamic market conditions. Thus, the dynamic capabilities of an organization describe the "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments […] to achieve new and innovative forms of competitive advantage" (Teece et al. 1997).

This theory consists of two key aspects, "dynamic" and "capability." While some authors relate "dynamic" to the ability to renew competences in the presence of changing environments, e.g., Teece et al. (1997), other authors equate the term also independent of market dynamism. They associate "dynamic" with the nature of the capability itself and argue for the use of dynamic capabilities to change existing routines, processes, resources or capabilities, i.e., being able to alter the way an organization solves problems (Zollo and Winter 2002; Helfat and Peteraf 2003; Winter 2003; Zahra et al. 2006). A recent meta-analysis underpins that dynamic capabilities are not necessarily manifested in environments with rapid (technological) change (Fainshmidt et al. 2016).

Teece et al. (1997) understand a "capability" as "appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences to match the requirements […]." In contrast to a resource, which is easily exchangeable between organizations, a capability is organization-specific (Makadok 2001). Moreover, capabilities are collections of routines (patterns of actions) that are repeatable and turn assets or resources into outputs of greater value (Wade and Hulland 2004; Makadok 2001; Pavlou and El Sawy 2011; Winter 2003). They include technical or managerial skills or processes like software development. Assets and resources are in this paper understood as anything tangible, i.e., physical (e.g., personnel, machinery or IT hardware) or intangible (e.g., software or patents) that an organization can use to develop, produce, and offer its products or services and that is not organization-specific (Wade and Hulland 2004; Makadok 2001; Nevo and Wade 2010).

Summarizing, we understand dynamic capabilities as organization-specific capabilities used to extend, modify, change, and/or create assets and resources to enhance value, particularly but not necessarily in dynamic environments (Collis 1994; Dosi et al. 2000; Winter 2003; Hoopes and Madsen 2008; Drnevich and Kriauciunas 2011; Makadok 2001; Pavlou and El Sawy 2011; Wade and Hulland 2004). Applying this understanding, we consider an enterprise resource planning system (ERP) purchased from external software vendor as an information and communication technology (ICT) asset of an organization. With increasing use of such ICT assets, a company must build up (ordinary) capabilities to maintain, govern and manage the systems. To leverage the full potential of such ICT assets, the (dynamic) capabilities to configure it to organizations specifics, to re-shape it when needed, to extract data for analytics, etc., become crucial value drivers in a dynamic environment.

2.4 From dynamic capabilities in information systems towards dynamic business intelligence capabilities

RBV first appeared in the mid-1990s in IS research and was thereupon extensively used in this field. Most of the work explained how information technology (IT) provides value and competitive advantage for organizations. Existing work identified the contribution of IT assets to business value either through a direct link (Aral and Weill 2007) or through the interaction of (IS resources based on) IT assets and other organizational resources (Wade and Hulland 2004; Cosic et al. 2012). Hence, IS capabilities are the combination of IT assets and other organizational resources, including people, technology and processes (Wade and Hulland 2004; Olszak 2014). Mikalef et al. (2016) recently identified a direct impact on flexible IT to competitive performance as well as that moderated by IT-enabled dynamic capabilities. Yet the role of dynamic capabilities in IT and IS was not only applied in general, but also to specific topics and a wide range of areas. For instance, Drnevich and Kriauciunas (2011) analyzed, amongst others, the use of IT to develop new products or services, whereas Daniel and Wilson (2003) investigated necessary dynamic capabilities in e-business transformations. Regarding the field of BI, exemplary assets are BI tools or technologies used for BI. If these assets are configured to solve the problems of an organization, e.g., by information gathering and the preparation to make better decisions, they turn into BI capabilities. Thus, an initial understanding of BI capabilities is the ability to build, reconfigure, integrate and manage BI assets combined with other (tangible or intangible) assets (such as people or processes) and transform them into assets of greater value, particularly but not necessarily in changing business environments. To deepen the understanding of dynamic BI capabilities, we further analyzed publications in leading IS journals (Knabke and Olbrich 2015a). We borrowed the methodology of a literature review in IS as described by vom Brocke et al. (2009) and Fettke (2006). Because of their acknowledged quality and centrality in the IS discipline, we focused on the Association for Information Systems (AIS) senior scholars' basket of journals, known as the "basket of eight" (Members of the Senior Scholars Consortium 2011). Additionally, we included the Strategic Management Journal as leading articles about RBV and dynamic capabilities have been published here, e.g., Wernerfelt (1984), Teece et al. (1997), Helfat and Peteraf (2003) or Winter (2003). All journals were assessed from their first issue to the most recent issue available in the respective electronic databases in January 2015. We used EBSCO to search for articles with the phrase

> ("dynamic capability" or "dynamic capabilities" or "dynamic resource based view") and ("information system" or "information systems" or "business intelligence" or "business analytics" or "data warehouse" or "DWH")

in the title or abstract. As we are especially interested in the overlap of dynamic capabilities and IS or BI in particular, one of the expressions in the first parentheses needs to occur with at least one expression in the second parentheses. This explains why not every journal in scope appears with matching articles in the result list in Table 1. This list reflects the understanding of the searched literatures authors' of dynamic capabilities in IS or BI.

We compiled an author-centric approach to identify concepts of dynamic capabilities (Webster and Watson 2002). Based on the identified dynamic capabilities, e.g., manufacturing capabilities (Banker et al. 2006) or customer sensing capability (Roberts and Grover 2012), we derived concepts of dynamic BI capabilities. The results are three concrete dynamic BI capabilities. These are an adoption of BI assets, achieving market understanding and intimacy with BI, and supporting business operations with BI. Table 2 summarizes the contribution of each article in a concept-centered matrix (Webster and Watson 2002).

Table 1 Summary of dynamic capabilities publications in an IS and BI context

References	Journal	Extant examples of dynamic capabilities
Banker et al. (2006)	MISQ	Manufacturing capabilities (just-in-time manufacturing, customer and supplier participation programs) by resource planning systems, operations management systems, electronic data interchange applications
Pavlou and El Sawy (2006)	ISR	Reconfigurability operationalized by market orientation (sensing the environment), absorptive capacity (learning), coordination capability (coordinating activities) and collective mind (integrating interaction patterns)
Butler and Murphy (2008)	JIT	Organizational and managerial processes, namely integration, learning, reconfiguration, and transformation
El Sawy et al. (2010)	ISR	Improvisational (spontaneous) capabilities (by project and resource management systems and collaboration work systems), planned dynamic capabilities (by organizational memory systems)
Kim et al. (2011)	JAIS	IT personnel expertise, IT infrastructure flexibility, IT management capability
Singh et al. (2011)	JAIS	Processes that learn, value-based governance, dynamic commitments, modular design
Roberts and Grover (2012)	JMIS	Customer agility as a dynamic capability consisting of customer sensing capability, agility alignment, and customer responding capability
Drnevich and Croson (2013)	MISQ	Match or create market change with processes for acquiring, integrating, reconfiguring, and/or releasing resources that produce a "first-order change" in the organization
Daniel et al. (2014)	JSIS	Business objectives drive projects, multiple and dynamic prioritization criteria, dynamic balancing of risk and reward, cancel/reconfigure in-flight projects

Table 2 Concept matrix of dynamic BI capabilities

References	Dynamic BI capabilities		
	Adoption of BI assets	Market understanding and intimacy with BI	Business operations with BI
Banker et al. (2006)	(X)	X	X
Pavlou and El Sawy (2006)	X	X	
Butler and Murphy (2008)	X		(X)
El Sawy et al. (2010)	(X)		(X)
Kim et al. (2011)	X		
Singh et al. (2011)			X
Roberts and Grover (2012)		X	
Drnevich and Croson (2013)		X	X
Daniel et al. (2014)	(X)		X

X: explicitly mentioned; (X): implicitly mentioned

We understand all three capabilities with regard to BI. Adoption of (BI) assets comprises the adoption and configuration of the used BI technology or the education of personnel working with BI as well as all tools used for BI and its applications. Market understanding and intimacy summarizes all knowledge and insight about customers, suppliers, etc., generated with BI. This capability addresses the view toward the outside of an organization whereas business operations reflect the internal view. This capability describes the support and enablement of business operations with by BI. All three identified dynamic BI capabilities explicitly include coordination, governance or organizational topics, as e.g., mentioned by Drnevich and Croson (2013) or Butler and Murphy (2008).

2.5 Dynamic BI capability: adoption of BI assets (AOA)

Technology was mentioned by several sources of the reviewed literature. IT and a flexible infrastructure are important for reacting to changing business conditions and for linking business and organizational functions to leverage synergies. It supports business strategies and structural changes and sustains competitiveness. To prepare and use technological assets, knowledgeable staff as another asset is required. The personnel need to understand the technology itself, the way to adapt and adopt it, and they require knowledge of the operation systems, programming languages, networks, databases, and an understanding of business functions. The use of technology and its adoption requires a dedicated management addressing coordination and communication efforts. These skills can then be applied to integrate information systems that timely route the relevant information to decision-makers (Roberts and Grover 2012; Kim et al. 2011). Organizations focus on separated projects and initiatives to reconfigure their assets accordingly and to meet external and internal requirements and align with business strategies (Daniel et al. 2014; Drnevich and Croson 2013). The assets of an organization, even if usually considered as commodities such as IT technologies, can turn into strategic value if they are configured to be unique (Butler and Murphy 2008; Wade and Hulland 2004).

We summarize these findings with the adoption of BI assets as the first construct of our research model. With BI as the field of our research we refer to the adoption of assets as the viable use of an organization's existing BI assets (say the database, the layered architecture, the extracted and cleansed data, etc.); in particular, the capability to manage (in a sense of rather steering and govern than maintaining), configure, and extend assets (use) as well as to reassemble them into new assets. We acknowledge that the distinction between ordinary and dynamic capabilities might seem fuzzy with AOA. Yet, putting special emphasis on the influence of modern ICT as the crucial role of ICT for adoption was highlighted by several authors, e.g., Kim et al. (2011) or Pavlou and El Sawy (2006).

2.6 Dynamic BI capability: market understanding and intimacy with BI (MUI)

Pavlou and El Sawy (2006) discovered that IT leveraging competence indirectly influences competitive advantage in the development of new products and services through functional competencies and dynamic capabilities. Furthermore, they show the importance of market orientation to address market and customer needs. Roberts and Grover (2012) identified how customer-based knowledge creation is important for sensing customer demands while analytical ability (understood as proactive BI) plays a major role in this context. They found that the integration of internal IS, storing e.g., order or customer data, and external IS, connected to business partners such as contractors or suppliers, is crucial for responding to customer requirements. Coordinating and governance abilities are important not only internally but also with rivals to restrict new market entrants or to assert power over suppliers and customers (Drnevich and Croson 2013).

Hence, we define the knowledge that an organization achieves with BI about itself, its position in the market, its performance, its products or services, its customers and suppliers, its competitors, new product developments as well as potential new market entrants, also known as Porter's five forces (Porter 1979), with the term market understanding and market intimacy.

2.7 Dynamic BI capability: business operations with BI (BO)

Singh et al. (2011) identify processes that learn as relevant for adapting to changing circumstances. They highlight the integration of dynamic capabilities into an organization's core processes. For Kim et al. (2011) IT expertise is crucial to support and redesign business processes adequately to changing market situations. They explicitly mention incorporating analytics and information into business processes. BI provides useful means to enable and improve strategic, tactical, and operational decision making and is therefore beneficial on all levels of an organization (Watson 2009; Marjanovic 2007). From an organizational structure perspective, IS enhance the value of organizational resources. Internally integrated, they support inter-functional coordination (Roberts and Grover 2012). With the coordination of organizational activities and production Butler and Murphy (2008) emphasize the importance of organizational and managerial processes.

We summarize this third identified dynamic BI capability as business operations. It comprises all primary, e.g., manufacturing, and auxiliary (accounting, HR, R&D, etc.) processes as mentioned by Banker et al. (2006) or Daniel et al. (2014). It focuses on the planning and execution activities that are supported by BI and are directly connected to the creation of products and services offered by an organization. As an acknowledged means of decision support, BI is suitable for supporting the decision-making process with its steps of intelligence, design, choice, and review (Simon 1977) and can be used to measure the performance of an organization or business processes.

The fourth construct and target to be analyzed is BI agility, as previously described.

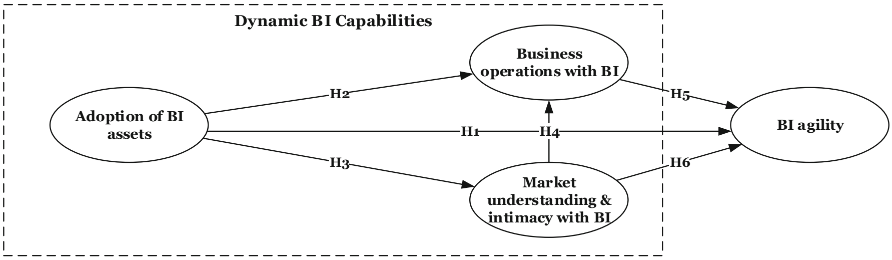

Fig. 2 Research model

3 Research model and hypotheses development

It is worth mentioning that BI agility in this paper is understood as a construct of several dimensions as described earlier (Fig. 1). Although concepts such as agile delivery methods, e.g., scrum, may influence dimensions like perceived customer value, they focus solely on the implementation process of BI. But the understanding of BI agility in this study goes way beyond this. We believe that the pure implementation of technological advancements as part of BI assets to achieve BI agility is necessary, but not sufficient. This transformation also depends on how technology is managed and integrated (Westerman et al. 2014). BI agility then results from facilitating advanced technological assets with leadership capabilities. Besides this direct effect (modeled as hypothesis H1 in Fig. 2), we hypothesize that BI assets like IMDB need to be appropriately adopted, combined, and integrated with business operations and market understanding (Fig. 2). These mediating effects via business operations and market understanding and intimacy are depicted as hypotheses H2, H3, H4, H5 and H6. Figure 2 summarizes the three identified dynamic BI capabilities and their connection to BI agility.[1]

3.1 Relationship between adoption of BI assets and BI agility

Tangible and intangible assets are crucial components of BI. Organizations require staff and corresponding structures to apply technologies and develop and integrate BI. Sensing, analyzing, and responding to changes are characteristics of agility and are important for business success (Sambamurthy et al. 2003; Overby et al. 2006). Sambamurthy et al. (2003) argue that IT investments influence the performance of a firm through (amongst others) agility. To successfully apply emerging technologies like IMDBs for BI, an organization needs to invest in that technology, teach its staff accordingly, integrate it into its technology stack, and adopt it for the use for BI. According to Drnevich and Croson (2013) IT is integral to business-level strategy. Thus, a viable use and adoption of technological assets will likely have a positive impact on the business model as one dimension of BI agility (see Fig. 1). In addition, there is evidence that new technological advancements like IM technology

[1] BI agility may then enable further concepts, e.g., sustainable corporate advantage. But, a study beyond BI agility is not in the scope of this paper.

bring various benefits for BI and might serve as a technology enabler for a more agile BI, e.g. by impacting its architecture (Knabke and Olbrich 2011; Plattner 2009). Hence, we deduct that the use and adoption of BI assets is an antecedent to BI agility and stipulate:

H1 Adoption of BI assets positively impacts BI agility.

3.2 Relationship between adoption of BI assets and business operations with BI

BI is an essential component of an organization's application landscape and is closely connected to action and decision-relevant information (Krawatzeck and Dinter 2015). If an organization can align its IT and BI activities with the overall business strategy, meet demands for business services, and implement reliable and cost-efficient BI applications, it can outperform competitors (Kim et al. 2011). In contrast, with a lack of this expertise, the redesign of processes and the enablement of business operations in changing environments will fail (Rockart et al. 1996; Kim et al. 2011). The postulation to integrate information into the core business processes (Kim et al. 2011) turns BI, its underlying technology, and the staff adopting it into a substantial part and antecedent of business operations. Hence, we argue that an organization's capability to adopt BI-related assets increases its capacity to improve business operations and hypothesize:

H2 Adoption of BI assets positively impacts business operations with BI.

3.3 Relationship between adoption of BI assets and market understanding and intimacy with BI

BI and analytical ability are necessary for a firm to be competitive in markets and achieve customer agility (Roberts and Grover 2012; Krawatzeck and Dinter 2015). The required expertise needs to be developed and shared throughout the organization to enable staff to become familiar with the use and adoption of existing and new BI and technology assets. Expanding professional knowledge and sharing this information throughout the organization is a slow but vital process that is hard to imitate and specific to each organization (Kim et al. 2011; Rockart et al. 1996). This expertise needs to be applied to use and adopt existing and new BI assets. BI and analytical abilities make a significant impact in creating knowledge of the customers and to achieve customer agility (Roberts and Grover 2012). Hence, we argue that BI assists organizations in gaining the required market understanding and intimacy and propose:

H3 Adoption of BI assets positively impacts market understanding and market intimacy with BI.

3.4 Relationship between market understanding and intimacy with BI and business operations with BI

Roberts and Grover (2012) discovered that analytical ability and thus BI are beneficial in the process of (customer) knowledge creation. Knowledge is the prerequisite to exerting power over market participants, such as customers or suppliers. Furthermore, market knowledge is required to shape core processes effectively. Pavlou and El Sawy (2006) identified that sensing the environment by market orientation impacts the reconfiguration of resources and the operational processes of an organization. BI, business analytics, and information should be integrated to business processes (Kim et al. 2011). As BI is a viable means to gaining market understanding this suggests that market orientation and, in particular, market understanding and intimacy is related to business operations and supported by BI. Hence, we hypothesize:

H4 Market understanding and market intimacy with BI positively impact business operations with BI.

3.5 Relationship between business operations with and BI agility

Business operations comprise all primary and auxiliary processes as well as the decisions supported by BI. BI that is integrated in business operations is closely connected to the business model of an organization which is a dimension of BI agility. As support, improvement, and the enablement of business processes are characteristics of an agile BI, a connection between business operations and BI agility appears obvious. Furthermore, if BI is well integrated in business operations it is likely to gain customer value. Changes regarding BI might be highly prioritized if they are integrated into business process as postulated by Kim et al. (2011) and are thus available in an adequate time frame. Therefore, we state:

H5 Business operations with BI positively impact BI agility.

3.6 Relationship between market understanding and intimacy with BI and BI agility

Market orientation addresses drivers of environmental change (Overby et al. 2006). Creating and applying information is thus important for responding to dynamic environments (Singh et al. 2011). IT leveraging competence enhances the market orientation skills of an organization and accelerates “the efficiency by which information is acquired by the environment” (Pavlou and El Sawy 2006). The absorption of information and — as a consequence — change are addressed in the dimension change absorption, whereas the efficiency and adequateness of information retrieval refers to the attributes of economy and quality of the BI agility dimension perceived customer value (see Fig. 1). With BI, market-oriented knowledge (Roberts and Grover 2012) can be created. This is the basis for sensing, analyzing and responding to changing environments which are key for BI agility in particular (Knabke and Olbrich 2013). Consequently, we hypothesize:

H6 Market understanding and market intimacy with BI positively impact BI agility.

4 Methodology

4.1 Development of measurement items

Since all constructs of our study, i.e., adoption of BI assets, market understanding and intimacy with BI, as well as business operations with BI, are newly developed and appropriated to the context of BI we could not draw from existing measurement scales. Hence, we developed new instruments for this study with the help of the guideline provided by DeVellis (2003). We achieved the constructs to be measured from a literature review in our research model (see Fig. 2). Second, we generated an initial item pool with more than 80 question items (without statistical items) and determined the measurement format. After reviewing our initial item pool we reduced it to a manageable size of 22 items. Besides these items that measure the four constructs as depicted in Fig. 2, we included 16 questions for statistical purposes and to gather background information such as the BI experience of the participants. In addition, seven free text fields are available. All constructs are modeled reflectively as they cause their indicators. Each construct is measured by multiple indicators.

We administered our proposed items within a pre-study with 16 BI experts from industry and science to limit the extent of errors (Spanos and Lioukas 2001) and to further develop and validate the measures of our constructs. Therefore, the participants executed and tested the online questionnaire and gave feedback to refine the questionnaire and measurement items. All construct-measuring items were presented with a 7-point Likert scale.[2] Table 3 gives an overview of the study's measurement items and the development of each scale.[3]

[2] The result of the measurement item validation from the pre-study is shown in Appendix G.

[3] For the questionnaire statements as well as the detailed literature sources for the items please refer to Appendix A, Table 10.

Table 3 Overview of measurement items

Construct Dimension	Definition	Item
Adoption of BI assets (AOA)	The ability to use and adopt BI assets	
Technology	The ability to adopt and integrate technologies to and with BI	AOA1
	Butler and Murphy (2008) accentuate the important capability to use, adapt, and adopt technologies. Transferred to the field of BI we achieve a measurement for technology adoption	
Staff	The staff's knowledge of BI, related technology, and their adoption	AOA2
	For the development of an item that reflects the skills required of an organization's staff we used the work of Kim et al. (2011) and Butler and Murphy (2008)	
Structure and coordination	The level at which organizational structures and coordination skills for technology adoption and integration to and with BI are available	AOA3
	The items of an existing study (Rivard et al. 2006) with relevance for BI were adopted to derive a scale for the coordination of resources and organization structures	
Strategy alignment	The level of alignment and support of initiatives for BI (and related technologies) with the overall organization's strategy	AOA4
	The importance of project and strategy alignment for asset adoption, e.g., Daniel et al. (2014), was incorporated in this item and adapted to BI	
Market understanding and intimacy with BI (MUI)	The ability to gain market insights with BI	
Performance	The level at which BI is used to measure the organization's performance	MUI1
	The scale for an organization's performance is framed to the context of BI based on Drnevich and Croson (2013), Kim et al. (2011) and Nucleus Research (2014)	
Customer Supplier Competitor Own products	The ability to use BI to gain customer and supplier knowledge, knowledge about competitors, and their products as well as knowledge about own products/services The items are based on Porter's five forces (Porter 1979, 2008) that were used earlier for measurement items (e.g., Spanos and Lioukas 2001)	MUI2 MUI3 MUI4 MUI5
Structure and coordination	The level at which organizational structures and coordination skills for data-driven market insights are available	MUI6
	Inspired by a study of Roberts and Grover (2012) this item was adopted with regard to data-driven insight generation based on BI	

Table 3 continued

Construct Dimension	Definition	Item
Business operations with BI (BO)	The organization's competence to support business operations, i.e., all primary and auxiliary processes with BI	
Decision-making	The ability to prepare decisions and review their outcome with BI	BO1 BO2
	Based on Simon's (1996, 1977) four phases in the decision-making process, i.e., intelligence, design, choice and review, we embraced scales used in previous research, e.g., Kohli et al. (2004), and derived two items for decision-making based on BI. Information gathering about a problem and designing a solution in terms of decision making preparation are reflected in item BO1. The choice and review phase of decision making are incorporated into item BO2. It includes the choice of a solution and the monitoring of the outcome, e.g., the actions taken based on the decision	
Hierarchical level	The level at which BI is used in organizations	BO3 BO4
	The value of BI on all levels within an organization, i.e., strategical, tactical, and operational (Marjanovic 2007; Evelson 2011) forms the basis for these items	BO5
Structure and coordination	The level at which there exists corresponding organizational structures and coordination skills to use and integrate BI with business operations	BO6
	This item focusses on the importance of organizational structures and coordination (e.g., Kim et al. 2011; Singh et al. 2011) with regard to data-driven insight generation with BI	
BI agility (BIA)	The ability of BI to cope with changing environments	
Change behavior	The way BI addresses change	BIA1
	The scale items for BI agility are based on the dimensions of the BI agility framework (see right column in Fig. 1). Change behavior deals with the creation of, proaction and reaction to as well as learning from change and (e.g., Conboy 2009; Dove 2005 or Galliers 2007)	
Perceived customer value	The extent of perceived BI value for customers	BIA2
	Conboy and Fitzgerald (2004) and Conboy (2009) emphasize perceived customer value (simplicity, economy, quality) that results in this item	
Change absorption	The level at which point in time changes can be absorbed with BI	BIA3
	This item covers the important role of time (Conboy 2009; Pankaj et al. 2009), i.e., when a change can be absorbed	
Change processing	The way changes are processed with and within BI	BIA4
	Change processing incorporates sensing, analyzing and responding to a change as for example mentioned by Pankaj et al. (2009)	
Model and infrastructure	An organization's data model and infrastructure according to BI	BIA5
	It summarizes the importance of the data model in terms of architecture (Zimmer et al. 2012; Caruso 2011) and its re-usability, re-configurability or scalability (Dove 2005)	

Table 3 continued

Construct Dimension	Definition	Item
Business model	The level at which BI facilitates the business model of an organization This item was derived based on Rouse (2007)	BIA6

All items together refer to their respective construct. The dimension is a logical grouping of the content, i.e., no single-item constructs

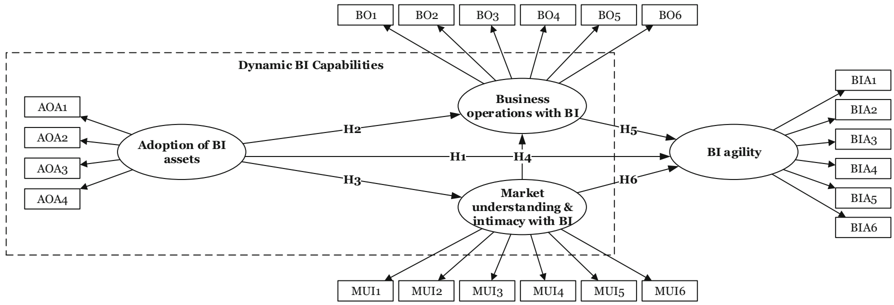

Fig. 3 Research model with items

Figure 3 recaps the research model including the measurement items as indicators of the constructs adoption of BI assets, market understanding and intimacy with BI, business operations with BI and BI agility.

4.2 Data collection and participants

The data was collected in a structured, self-administered survey (de Leeuw et al. 2008). The corresponding questionnaire was developed following the rules of Dillman et al. (2009). We used LimeSurvey hosted at www.limeservice.com to prepare and run our survey. Apart from statistical questions the answers in the questionnaire consisted of non-dichotomous rating scales (7-point Likert scales). With a survey-based approach participants' responses can be aggregated in a standardized manner and used for quantitative analysis (Bhattacherjee 2012).

Data was collected using several sources. First, we communicated our study through two business-oriented and one science-oriented social network. There, we posted our survey in 12 groups with topics around BI, analytics, data warehousing, and in-memory technology. In addition, we used the mailing lists of a global firm offering audit, tax, and consulting services. In this organization we addressed employees of the consulting service line based in Germany, Austria, and Switzerland. The mailing list contained 1122 people working in a variety of consulting fields such as strategy, management, risk, forensic, and technology consulting. The survey was open for nine weeks from November 2015 to January 2016. Overall, 342 people (30%) accessed the questionnaire and 110 participants completed the survey (32 or 10% of all persons contacted via mailing list, respectively). The participants had a technical, functional, management or science background and were spread across industries. 85 participants (77%) currently

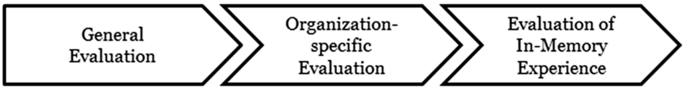

Fig. 4 Evaluation approach

work as consultants. All of the participants have at least 1 year's work experience, with 88 persons (80%) even having 6 or more years of experience.[4]

4.3 Evaluation approach

Obviously, it takes time for emerging technologies like IMDB to become pervasive, and most organization have used them and become experienced. We therefore need a sophisticated approach to analyze its impacts. Figure 4 illustrates the evaluation procedure that first analyzes the importance of a construct in general (general evaluation) before digging into the specific implementations in the participants' organizations (organization-specific evaluation). This allows for the analysis of how and whether pervasion of emerging technologies, here IMDB, is expected to take place. By additionally querying the concrete situation at the participant's organization, the question of whether expectations have been met can be answered. According to this approach, the statements to measure the constructs of the research model were split into twofold logic. First, we asked the participants to rate a statement in general, i.e., without reference to the organization they work for. Second, we asked them to assess their organization according to the given statement.

As a final step, the study identifies differences between experienced and non-experienced organizations with regard to in-memory technology. The comparison of the general evaluation and the organization-specific implementation as well as the differentiation between in-memory experiences is done with multigroup analysis (MGA). MGA allows us to detect specific effects in pre-defined data groups (Hair et al. 2014; Sarstedt et al. 2011).[5]

4.4 Common method bias

Common method bias (CMB) is a potential problem in survey research (Podsakoff et al. 2003). We assessed the collected data with ex-post statistical analysis to identify bias (Chen and Siau 2012; Urbach and Ahlemann 2010; Podsakoff et al. 2003). Correlation analysis as a useful means to determine common method bias (Pavlou et al. 2007; Chen and Siau 2012; Bagozzi et al. 1991) resulted in 0.73 (general view) and 0.83 (organization-specific implementations) as the highest correlation among the constructs in this study. These values are below the recommended threshold of 0.9 for CMB (Pavlou et al. 2007; Chen and Siau 2012). Thus, we conclude that no CMB exists.[6]

[4] Tables 11 and 12 in Appendix B provide detailed information about the participants.

[5] Below, the steps general evaluation and organization-specific evaluation are also referred to as general view and organization-specific implementations.

[6] See Appendix C for details.

5 Results

We evaluated our research model using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 2 and SmartPLS 3 as a software tool (Ringle et al. 2005, 2015). It is an appropriate and acknowledged method for testing and estimating causal relations in the field of IS (Gefen et al. 2000; Urbach and Ahlemann 2010). In particular, PLS is superior to covariance-based methods if studies have a small sample size, the investigated phenomenon is new and measurement models need to be newly developed (Urbach and Ahlemann 2010). Sample size is a central topic for quantitative research and is particularly relevant for PLS-SEM (Marcoulides and Saunders 2006; Urbach and Ahlemann 2010). Following the often-cited 10 times rule a minimum sample size of 30 is required for testing the presented research model (Hair et al. 2011; Urbach and Ahlemann 2010). However, Hair et al. (2017) recommend a more differentiated consideration of the sample size against model and data characteristics. More specifically, with a number of three independent variables in the longest structural path, the required sample size is 103 based on the commonly used level of statistical power of 80% for detecting R^2 values of at least 0.1 with an error probability of 5%. Thus, we deem this study's sample size of $n = 110$ acceptable.

5.1 Validation of constructs

We first assessed the validity and reliability of our outer model. Urbach and Ahlemann (2010) suggested various validations testing for reflective measurement models. We verified our constructs based on their guidelines and assessed the indicator reliability, the internal consistency reliability using Cronbach's alpha (CA), and the composite reliability (CR), convergent validity, and discriminant validity with cross-loadings and the Fornell–Larcker criterion. All indicators meet the criteria for outer loadings of 0.7 or higher at a significance level of 0.01 or better (Hair et al. 2011, 2014; Henseler et al. 2009; Urbach and Ahlemann 2010). Only one loading (BIA6 with 0.67) for the general view is below the threshold of 0.7. According to Hulland (1999) only items with loadings below 0.4 or 0.5 should be dropped. Hence, they are deemed reliable. The criteria for CA and CR are met with values higher than 0.7 (Urbach and Ahlemann 2010; Nunnally and Bernstein 2010). As all values for the average variance extracted (AVE) are above 0.5 the criterion for convergent validity is fulfilled (Urbach and Ahlemann 2010; Hair et al. 2014). Finally, discriminant validity is met as the square root of a construct's AVE is higher than the correlation with any other construct (Fornell–Larcker criterion). Furthermore, no cross-loadings exist as the difference between an item's own loading and the loading on other constructs is at least 0.1 (Gefen and Straub 2005). Only one item (BIA6) does not meet this criterion for the general view (see Appendix D) But, as the difference is 0.07 and the Fornell–Larcker criterion is fulfilled we refer to the discriminant validity as satisfactory. Particularly, as the recently introduced heterotrait-monotrait (HTMT) ratio of correlations criterion for assessing discriminant validity is also fulfilled (Henseler et al. 2015). Statistical power is another important measure for PLS-SEM analysis (Aguirre-Urreta and Rönkkö 2015). All values in this

Table 4 Internal consistency, convergent reliability, discriminant validity and statistical power (general view)

Construct	Cronbach's alpha (CA)	Composite reliability (CR)	Convergent reliability (AVE)	Discriminant validity				Observed statistical power
				AOA	MUI	BO	BIA	
AOA	0.85	0.90	0.70	**0.83**				
MUI	0.87	0.90	0.60	0.55	**0.78**			0.99
BO	0.90	0.92	0.67	0.54	0.73	**0.82**		1.00
BIA	0.87	0.91	0.62	0.45	0.64	0.72	**0.79**	1.00

The diagonal elements (in bold) for the discriminant validity test are the square roots of AVEs; correlations are off-diagonal. p level is 0.01 for observed statistical power

Table 5 Internal consistency, convergent reliability, discriminant validity, and statistical power (organization-specific view)

Construct	Cronbach's alpha (CA)	Composite reliability (CR)	Convergent reliability (AVE)	Discriminant validity				Observed statistical power
				AOA	MUI	BO	BIA	
AOA	0.87	0.91	0.71	**0.85**				
MUI	0.89	0.91	0.64	0.71	**0.80**			1.00
BO	0.92	0.94	0.72	0.72	0.83	**0.85**		1.00
BIA	0.94	0.95	0.76	0.72	0.74	0.83	**0.87**	1.00

The diagonal elements (in bold) for the discriminant validity test are the square roots of AVEs; correlations are off-diagonal. p level is 0.01 for observed statistical power

study are above the threshold of 0.8 (Aguirre-Urreta and Rönkkö 2015; Akter et al. 2011; Cohen 1988; Soper 2017). Table 4 summarizes the results.[7]

For organization-specific implementations all indicators meet the criteria for outer loadings as well as for CA, CR and AVE. Discriminant validity is deemed acceptable as no cross-loadings exist and the difference for MUI6 (0.08) and BIA1 (0.09) is just slightly below the threshold of 0.1. Furthermore, the HTMT ratio for discriminant validity is fulfilled. Table 5 shows the results for the organization-specific view.[8]

5.2 Hypotheses testing

After confirming the adequateness of the outer measurement model we tested the proposed hypotheses. Hence, we examined the structural path model by analyzing the path coefficients (β) and their significance. We used bootstrapping to test the significance of the path coefficients with 5000 bootstrap runs and 110 as the number

[7] Further details are shown in Appendix D.

[8] Further details are available in Appendix E.

of cases which are equal to the number of observations (Hair et al. 2011). One-tailed tests were used to analyze the significance of the hypotheses as we hypothesized the directional effects (Köffer et al. 2015; Li et al. 2013). The model was further assessed for robustness by including the size of the organization as a control variable. It was operationalized by the number of employees and does not have an impact on the results.[9]

5.2.1 General evaluation

Figure 5 summarizes the path coefficients and significance levels in the structural model ($n = 110$). It shows that AOA has no significant impact on BIA ($\beta = 0.039, ns$). But, we identified that the impact of AOA on BO has a significant effect ($\beta = 0.192$, $p < 0.05$) and that the effect of AOA on MUI is also positively significant ($\beta = 0.552$, $p < 0.01$). MUI has a positive significant impact on BO ($\beta = 0.624$, $p < 0.01$). The direct effect of MUI on BIA ($\beta = 0.231, p < 0.1$) is also positively significant. Finally, BO has a significant impact on BIA ($\beta = 0.534$, $p < 0.01$). Thus, hypotheses H2, H3, H4, H5, and H6 are supported whereas H1 is not supported for the general view.[10] But, an impact of the adoption of assets exists via the mediators MUI and BO.

Furthermore, we investigated the amount of variance explained (R^2), also known as the coefficient of determination. It measures the explained variance of endogenous latent variables and indicates the predictive accuracy of a model. R^2 accounts for 31% for the dependent variable market understanding and intimacy and 56% for business operations. For the dependent variable BI agility it is 55%. As a rule of thumb from marketing research Hair et al. (2011) describe 0.75, 0.50, and 0.25 as values for R^2 as substantial, moderate or weak. In an empirical application of PLS, Chin (1998) mentions lower values of 0.67, 0.33, and 0.19 for R^2 in his example as substantial, moderate, and weak levels, respectively. Falk and Miller (1992) recommend a minimum value of 0.1 for R^2. An R^2 value below this threshold is substantively meaningless even if statistically significant in their opinion. Accordingly, the values of our study are deemed acceptable and are at a weak and moderate level according to the most restrictive boundaries of Hair et al. (2011).

Figure 5 shows the direct effects between constructs. As our model does not only include direct relationships, the indirect effects and total effects as the sum of direct and indirect effects are taken into account (Henseler et al. 2009).[11] Table 6 shows that all total effects are significant. AOA has a significant positive total effect on BO ($\beta = 0.536$, $p < 0.01$) via its direct path H2 and indirect paths H3 and H4. Although H1 was not impacting BIA directly for the general view, it has a significant impacting by taking the mediators MUI and BO into account. Here, AOA is

[9] Details for the model evaluation with controlled organization size can be found in Appendix H.

[10] Further details of the model validation are shown in Appendix D.

[11] Indirect effects represent a relationship between constructs via a third construct, e.g., a mediator. If x is the path coefficient between an independent and a mediator variable and y is the path coefficient between the mediator variable and the dependent variable, the indirect effect is the product of x and y. If only one path exists between two variables the total effect equals the direct effect.

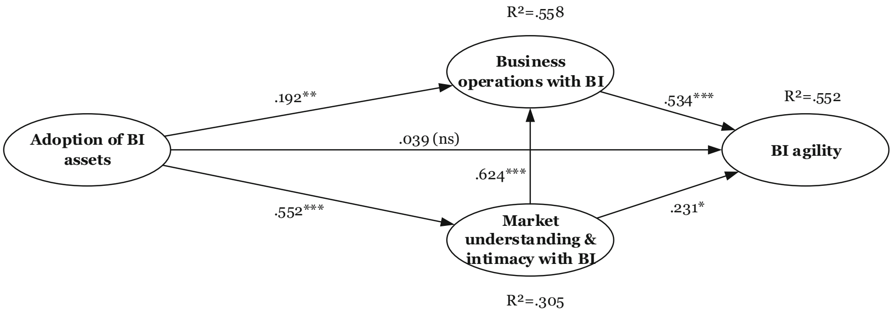

Fig. 5 Analysis results for the general view. *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

Table 6 Mediation and significance analysis of the direct, indirect and total effects (general view)

Relationship	Direct effect	t value	Indirect effect	t value	Total effect	t value
AOA → MUI	0.552***	6.283			0.552***	6.283
AOA → BO	0.192**	1.781	0.344***	5.002	0.536***	4.771
AOA → BIA	0.039^{ns}	0.380	0.414***	4.968	0.453***	3.628
MUI → BO	0.624***	7.158			0.624***	7.158
MUI → BIA	0.231*	1.451	0.333***	2.720	0.564***	5.997
BO → BIA	0.534***	3.090			0.534***	3.090

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

significantly impacting BIA ($\beta = 0.453$, $p < 0.01$). MUI has a significant impact on BIA ($\beta = 0.564$, $p < 0.01$) via BO (H4, H5) and its direct path H6.

The research model hypothesizes a mediation effect of MUI and BO. We analyzed the effect of mediation by following the guidelines of Hair et al. (2017). The indirect effects in Tables 6 and 18 show a significant (indirect) relation between AOA and BIA. As the direct effect between AOA and BIA is weak and not significant, we conclude a full mediation effect (Hair et al. 2017).

5.2.2 *Evaluation of organization-specific implementations*

Figure 6 illustrates the coefficients of the organizations the participants are working for ($n = 110$). Consultants were asked to rate their client according to their use of BI and IM. The figure shows that all paths except from MUI to BIA are positive significant. Compared to the expectations in general (Fig. 5) the path from AOA to BIA ($\beta = 0.228$, $p < 0.1$) is also positive significant, but the path from MUI to BIA is not significant ($\beta = 0.088$, *ns*). In this consideration of organization-specific implementations only hypothesis H6 is not supported. R^2 accounts for 51% of the dependent variable MUI and 72% of business operations. For the dependent variable

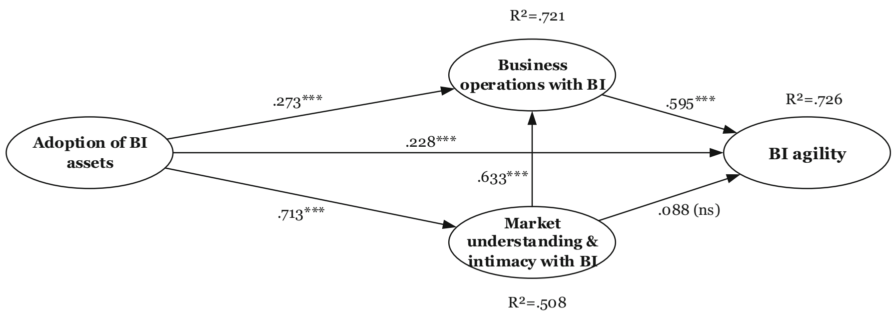

Fig. 6 Hypotheses test for the organization-specific view. *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

Table 7 Mediation and significance analysis of the direct, indirect and total effects (organization-specific view)

Relationship	Direct effect	*t* value	Indirect effect	*t* value	Total effect	*t* value
AOA → MUI	0.713***	15.786			0.713***	15.786
AOA → BO	0.273***	2.708	0.451***	7.041	0.724***	12.373
AOA → BIA	0.228***	2.470	0.494***	7.595	0.722***	12.571
MUI → BO	0.633***	8.031			0.633***	8.031
MUI → BIA	0.088^{ns}	0.928	0.376***	5.078	0.465***	5.165
BO → BIA	0.595***	6.901			0.595***	6.901

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

BI agility it has the highest value with 73%. Thus, all constructs are at a moderate level (Hair et al. 2011). Following the metrics of Chin (1998), BO and BIA are even at a substantial level.[12]

Again, all total effects toward BI agility are significantly positive (Table 7). The indirect effect for AOA on BI is also positive (see Tables 7, 22). But, in this case the direct relationship between AOA and BO is significant. As the product of the path coefficients of H2 and H5 is positive significant, we conclude that BO complementary mediates the relationship between AOA and BIA. Furthermore, the product of the coefficients of H3, H4 and H5 is positive significant. However, the product of the coefficients of H3 and H6 is positive, but not significant. Hence, we argue that MUI does only represent a mediator for the relationship between AOA and BIA on the structural path AOA → MUI → BO → BIA but not for the path AOA → MUI → BIA. Summarizing, MUI and BO represent complementary mediation of the relationship from AOA to BIA (Hair et al. 2017).

Table 8 shows the difference between the overall importance (or expectation) of a construct in general (Fig. 5) and the organization-specific implementation (Fig. 6) as the result of a group comparison. We used a parametric approach for PLS-SEM

[12] Further details of the model validation are shown in Appendix E.

Table 8 Group comparison (general vs. organization-specific view)

Relationship	Path coefficients from PLS (organization vs. general)	Difference in path coefficients
AOA → BIA (H1)	0.228*** versus 0.039^{ns}	0.189*
AOA → BO (H2)	0.273*** versus 0.192**	0.081^{ns}
AOA → MUI (H3)	0.713*** versus 0.552***	0.161*
BO → BIA (H4)	0.633*** versus 0.624***	0.061^{ns}
MUI → BIA (H5)	0.088^{ns} versus 0.231*	−0.143^{ns}
MUI → BO (H6)	0.595*** versus 0.534***	0.009^{ns}

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

multigroup analysis (PLS-MGA) as described by Hair et al. (2014) for unequal standard errors. Table 8 illustrates that there is a significant positive difference for hypotheses H1 and H3 if the general importance of dynamic capabilities in a BI context is compared to organization-specific implementations. On an organizational level the impact of AOA on BIA by far exceeds the expectations of the participants in general ($\beta_{\mathrm{Org}} = 0.228$ vs. $\beta_{\mathrm{Gen}} = 0.039$, $d = 0.189$, $p < 0.1$) with β_{Org} and β_{Gen} as the path coefficients for the organizational and general view respectively. The difference in path coefficients is held by d. Another significant difference was identified between AOA and MUI ($\beta_{\mathrm{Org}} = 0.713$ vs. $\beta_{\mathrm{Gen}} = 0.552$, $d = 0.161$, $p < 0.1$).

5.2.3 *Impact of in-memory experience*

To analyze the effect of IM technology, we compared organizations that do not use IM technology to organizations experienced with this technology for BI. The first group (“exp. IM Org.”) consists of participants that work at organizations that have been using IM technology for BI for at least three years. We took the organization-specific view for this group ($n = 39$), i.e., the rating of statements according to their organization. In contrast, the second group (“no IM Org.”) contains participants that work at organizations with no IM technology for BI at all. For this second group ($n = 31$) we analyzed their expectations, i.e., general view. This confronts the participant’s expectations of the influence of IMDB with the actual outcome of in-memory technology implementations in organizations.

Table 9 shows the result of this group comparison (Hair et al. 2014). The analysis identifies two significant positive differences. For hypothesis H1 the difference is 0.365 and turned from negative to positive ($\beta_{\mathrm{Org}} = 0.286$ vs. $\beta_{\mathrm{Gen}} = -0.079$, $d = 0.365$, $p < 0.1$). H3 also had a positive significant difference for long IM use at organizations compared to the expectations of participants working for organizations with no IM use at all ($\beta_{\mathrm{Org}} = 0.720$ vs. $\beta_{\mathrm{Gen}} = -0.243$, $d = 0.167$, $p < 0.1$).[13]

[13] Further details can be found in Appendix F.

Table 9 Group comparison (experienced IM organizations vs. organizations with no IM use)

Relationship	Path coefficients from PLS (exp. IM org. vs. no IM org.)	Difference in path coefficients[a]
AOA → BIA (H1)	0.286* versus −0.079^{ns}	0.365*
AOA → BO (H2)	0.404*** versus 0.243*	0.161^{ns}
AOA → MUI (H3)	0.720*** versus 0.552***	0.167*
BO → BIA (H4)	0.520** versus 0.871***	−0.351^{ns}
MUI → BIA (H5)	0.096^{ns} versus 0.044^{ns}	0.052^{ns}
MUI → BO (H6)	0.581*** versus 0.603***	−0.023^{ns}

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

[a] Deviations due to rounding

6 Discussion and interpretation

The empirical investigation uncovered new findings of influence factors for BI agility. We quantified the relationship among the adoption of BI assets with explicit respect to technological advancements, the external (market understanding and intimacy) and internal (business operations) view of an organization as well as BI agility. Our results show that each of the constructs influences BI agility, either directly or indirectly. The adoption of BI, technology and human resource assets positively influences both external (MUI) and internal operations (BO). In addition, AOA has a significant impact on BI agility via BO (H2, H5) as well as via the connection between MUI and BO (H3, H4, H5). This path (H3, H4, H5) is strongly significant with high coefficients for both, the general and the organization-specific view, and is therefore called the "agility path." It shows that a close integration of technology and BI (AOA) is useful for generating insights from outside the organization (MUI) and using them to optimize internal processes (BO), finally resulting in BI agility. For instance, Knabke et al. (2014, 2015) provide an example of these implications for managerial practice.

Apparently, the participants in general believe that the pure use of technology and the according adoption of BI assets (H1) do not have an impact on BI agility. Without using IM technology as a basis for BI, organizations seem to underestimate its direct potential. Indeed, the positive impacts on data integration without redundant physical storage, improved data staging and provisioning as well as lightweight DWH-based BI architectures are not necessarily obvious until IM technology is used. Instead, the impact of AOA on BIA is mediated through MUI and BO in the general evaluation. AOA directly influences BIA when looking at organization-specific implementations (Fig. 6). Organizations using IM-technology as a basis for BI may have already realized the positive effects on the lightweight architectures possible with this technology. This interpretation is supported by the significance positive difference that organizations using IMDB for BI for three years or longer report, compared to organizations not using this technology at all (see Table 9). Another possible explanation for the positive effect (see Tables 8, 9) is increased perceived customer value as long-lasting data provisioning can be executed faster and more frequently. But, asset adoption and IMDB as technology enablers for an agile BI can only be part of the answer – integration into external and internal processes should not be neglected.

Compared to the general view, hypothesis H6 is not supported at the participant's organization. The necessity for change often arises outside the organization. Participants of the study mentioned that the behavior modifications of customers need to be quickly identified. These external insights need to be integrated into internal operations to adequately adapt and provide tailored solutions. This results in improved support of the business model with BI and increased customer value.

Summarizing, the findings indicate that to achieve BI agility emerging technologies like IM technology and their adoption, well-educated staff, corresponding structures, and strategy alignment are essential. The group comparison between general expectation and implementations at organizations emphasizes this observation (see Table 8). This is even intensified when analyzing organizations that have been using IM technology for three or more years (see Table 9). Additionally, the study shows that the use of BI and IM technology positively influences the generation of market insights, e.g., about customers or suppliers, as well as the support and enablement of business operations.

6.1 Implications for practice

The findings of our study have several implications for practitioners. First, IM technology seems to be a technology enabler for an agile BI. This effect is especially visible if the analyzed group is separated according to IM experience (see Table 9). Asset adoption has a slightly negative impact (-0.079, $p < 0.1$) on BI agility for organizations that do not use IM technology for BI. In contrast, the adoption of BI assets and the use of IMDB have a positive impact (0.286, $p < 0.1$) in organizations that have been using this technology for three years or longer for BI. IMDB as a basis for BI allows for simplified architectures and data models that are more flexible and adaptable to changes. For instance, layers only required for performance reasons become obsolete. This results in improved change behavior and higher perceived value for customers. An industry case study at a world's leading sportswear company confirms this finding (Knabke and Olbrich 2015b). Focusing on technology and keeping the education of staff, adequate structures as well as the integration of overall strategies in mind, the free text answers of the survey participants support this observation. Nine comments mention technology as an agility driver, which is the second-most answer. Especially for organizations that act in turbulent environments and need a BI set-up more agile than their competitors, users explicitly mention that IM technologies can bridge this agility gap. As 23 participants mention dynamic environments and changing requirements as the number one agility driver in their comments, the adoption of assets and a special focus on technology seems to be important. According to a member of the senior IT management, who was formerly responsible for BI at one of the world's leading sportswear companies, fast change will move from exception to normality and BI has to be ready to adopt to it. But, organizations need to overcome initial hurdles to transform technological assets into BI capabilities. A recent study from Limaj et al. (2016) supports this finding. They argue that the communal and shared utilization of a technology feeds dynamic capabilities, which is contrary to the often proposed assumption that IT/IS capabilities affect use.

Thus, as the second outcome of the study, the findings remind executives that technology should not be considered in isolation. The technology underlying BI has to be adopted specifically for each organization and it requires great effort in educating staff to accomplish this so as to get sustainable value from the investment. Moreover, suitable organizational structures as well as integrated strategies and activities are necessary to achieve BI agility. These results are confirmed by other studies, e.g., by Westerman et al. (2014). Participants of our study highlight numb organizations and structures as the characteristic that most prevents agility. This should be a motivation to strengthen BI initiatives and implement flexible structures. Budget and people, especially their skills and know-how, were identified by survey participants as further important fields of avoiding BI agility, which indicates a lack of importance and attention for BI initiatives in organizations. Especially as adequately adopted and integrated technology, well-trained staff, corresponding organizational structures, and the alignment of projects and initiatives with the overall strategy of the business may help to bridge the gap between operational activities and the supply of information as a basis for decision-making. Streamlined BI architectures using IM technology provide flexibility to adapt and analyze (additional) data sources as well as to configure BI and analytical capabilities to support market analysis and gain market understanding (H3). Improved market understanding positively influences the way business is operated (H4). For example, using BI to sense a change in customer buying behavior can trigger an adaption of business processes to stay competitive.

Consequently, the importance of using and adopting BI to achieve market understanding and intimacy, as well as to support business operations, is highlighted as the third result. The use of BI and IM technology exceeds expectations regarding the influence on external market view and internal operations. Using technological advancements and BI supports the generation of market insights. This knowledge can be applied to improve or enable business operations. Hence, market orientation and business operations have to be the guidelines to achieve BI agility. This is emphasized by the agility path (H3, H4, H5) in both observations. The integration of BI for the external view of an organization (market understanding and intimacy) is beneficial for its internal view (business operations) shown with the confirmation of H4. But, the optimization of business processes is not restricted to insights gained from outside. BI as a performance measurement instrument supports identifying weaknesses such as low-performing processes (H2 and indirect via H3, H4). The positive influence of market understanding and intimacy for BI agility is supported indirectly via business operations that positively impact BI agility (H4, H5). BI makes information gathering and the preparation of decisions transparent and allows for measuring the success of actions taken. This identifies relevant changes in the environment and as a basis for a response.

Fourth, our study contributes to an ongoing challenge for organizations. Table 8 shows that implementations for BI and the adoption of assets differ from the general expectations. Implementations at organizations seem to exceed the expectations from using BI and their corresponding assets (except for H6). IT executives and policymakers may draw on these results to evaluate their BI and asset adoption strategies. BI is not only an instrument to reflect history but provides valuable means to actively shape the future and align organizations for future developments and customer demands. Figure 6 and Tables 8 and 9 illustrate that the use of technological advancements like IMDBs and the according adoption of assets have a significant impact on achieving BI agility, both directly and indirectly via market understanding and intimacy and business operations.

6.2 Implications for research

This empirical study sheds light on how to achieve BI agility using the theoretical lens of dynamic capabilities. First, it provides a theoretical foundation to argue for the importance of asset adoption and the integration of an organization's external and internal view to achieve a more agile supply of information and decision preparation. We therefore derived dynamic capabilities in the field of BI on the basis of a structured literature review and connected them amongst each other and to BI agility. Moreover, our work provides a quantification of the impact on BI agility and paves the way for more empirical research in the field of BI agility based on dynamic capabilities theory.

Second, by theorizing that the adoption of assets plays an important role during the endeavor toward BI agility, we made a first attempt in analyzing the impact of technological assets. We started with a look at the impact of IM technology as it is a key technology for BI. From this study it is clear that IM technology has an impact on BI agility, but it needs to be adopted by well-educated staff and integrated into the organization's core processes to become beneficial. Supported by the work of Limaj et al. (2016), the utilization of technology, here IM technology, feeds dynamic capabilities.

Third, we made an industry-spanning attempt (see Appendix B) to analyze BI agility impact factors. Although prior publications presented mixed results of the success and benefits of BI (Xu and Hwang 2007; Shin 2003), we found that BI provides value for organizations, e.g., by supporting market orientation, intimacy, and business operations. Nevertheless, some organizations may not have harvested the fruits of BI and technology investments. In particular, although several participants mentioned changing regulatory requirements as one driver for agility, specific regulatory requirement, such as those, for example, in financial industries like banking, seem to prevent BI agility.

Fourth, we provided new measurement instruments in the field of BI for the adoption of assets, market understanding and intimacy, business operations, and agility. These measures are anchored in the literature and may serve other researchers in their studies.

7 Conclusion

Our study theorizes and applies the concept of dynamic capabilities to the field of BI. In particular, it contributes to agility in the context of BI and identifies antecedents of BI agility. Drawing on a structured literature review we identified three dynamic BI capabilities, i.e., the adoption of assets, market understanding and intimacy, and business operations, related to BI agility. We assessed the relation among these constructs using SEM-PLS. One empirical study with a twofold investigation was conducted in addition to one preliminary study validating the survey and the measures for the four constructs of our research model. The main study tested the research model and hypotheses in a questionnaire-based survey with 110 participants from different industries. We found that the adoption of (BI) assets has a significant impact on business operations and also market understanding and intimacy. Both constructs impact BI agility, whereas market understanding and intimacy also influence business operations. Digging from this general view into an analysis at an organization-specific level we show that BI implementations seem to exceed expectations. In particular, in the analysis considering the participant's organizations, we identified how the adoption of assets has a direct impact on BI agility. A second major result is the role of IM technology for achieving BI agility. Comparing organizations that do not use IMDB with organizations that have been using IM technology for three or more years for BI resulted in significant positive differences for the accomplishment of an agile BI. It highlights the importance of integrating new technological advancements and BI to internal and external processes. Beyond technological know-how, skilled personnel and organizational structures that cope with changing environments are crucial for achieving this integration. Managing this integration and embracing technological capabilities is a considerable step toward change readiness for BI.

Our presented results should be viewed in light of the studies' limitations. First, we build our understanding of dynamic BI capabilities on the existing literature at the intersection of the fields of strategic management, information systems, and business intelligence. Thus, we might not have assessed every relevant publication due to the nature of a literature review. We also acknowledge that these concepts might not be mutually exclusive. Second, as we conducted an industry-spanning analysis, our results should be applied with care to specific industries. Some industries may have distinct conditions, such as, for example, regulatory requirements known from the financial service industry. For example, one participant in our survey highlighted that the majority of IS investments in banking are spent to fulfill regulatory requirements. In addition, some organizations may not have developed the right strategies according to their industry conditions. Future research may build upon these findings and explore specific industries. Third, although we did not include geographical restrictions, most of the participants are based in Germany (88%). As the adoption of technologies may have a different pace in other countries or cultures, the results may differ if the study is conducted in other countries or cultures. Fourth, 77% of the participants work as consultants. Although consultants may be among the first to introduce new concepts and technologies, they might have a different, biased view of our constructs than industry practitioners. Fifth, we only considered antecedents and impacts on BI agility. With BI as the basis for decision support, this research does not identify how BI agility and the quality or timeliness of decision support are connected. Sixth, we focused on IM databases as one important technology enabler for BI. Nevertheless, we suggest that future research investigates further technologies (e.g., mobile devices or collaboration tools) and concepts (e.g., sourcing, analytics services) to achieve BI agility. Seventh, we tried to capture a complex phenomenon like BI agility by means of a quantitative approach. In our view this should be viewed as an early attempt in the field rather than as a 'silver bullet.' Consequently, we are looking forward to the reflection of our results in light of future discoveries and humbly hope we have offered research opportunities for future generations.

Appendix A: Survey measures

Table 10 contains the items of our constructs and literature sources. All items are presented on a 7-point Likert scale. First, the rating about the importance in general is asked for the item. Second, the participants are asked to rate their organization.

We are well aware of the discussion about the pros and cons of "don't know responses" (Beatty et al. 1998; Dillman et al. 2009). As the respondents' best subjective estimation adds value to our analysis, and to avoid missing values, we used mandatory questions in the survey.

Table 10 Survey measures

Item	Statement questionnaire	Sources for direct and indirect support
Adoption of BI assets		
AOAG1	The capability to use and adopt an organization's core assets to operate in today's business environments is important for organizations in general	For validation purposes
	The capability to use and adopt an organization's core assets to operate in today's business environments is sufficient in our (client's) organization	
AOAG2	The capability to use and adopt an organization's BI assets to operate in today's business environments is important for organizations in general	
	The capability to use and adopt an organization's BI assets to operate in today's business environments is sufficient in our (client's) organization	
AOAG3	The capability to use and adopt an organization's BI and underlying technology assets to operate in today's business environments is important for organizations in general	
	The capability to use and adopt an organization's BI and underlying technology assets to operate in today's business environments is sufficient in our (client's) organization	
AOA1	The capability to adopt and integrate new technological developments, e.g., IM technology, to the existing technology stack for BI is important for organizations in general	Banker et al. (2006) Butler and Murphy (2008) Kim et al. (2011) Knabke and Olbrich (2011)
	The capability to adopt and integrate new technological developments, e.g., IM technology, to the existing technology stack for BI is sufficient in our (client's) organization	Plattner and Zeier (2011) Roberts and Grover (2012) Knabke et al. (2014)
AOA2	Well-trained staff to integrate existing technologies with BI and adopt new technologies to BI is important for organizations in general	Butler and Murphy (2008) Kim et al. (2011) and Singh et al. (2011)
	Well-trained staff to integrate existing technologies with BI and adopt new technologies to BI is working in our (client's) organization	
AOA3	Corresponding organizational structures and coordination skills in order to integrate existing technologies with BI and adopt new technologies to BI are sufficient in our (client's) organization	Roberts and Grover (2012) Drnevich and Croson (2013) Pavlou and El Sawy (2006)
	Corresponding organizational structures and coordination skills in order to integrate existing technologies with BI and adopt new technologies to BI are important for organizations in general	Butler and Murphy (2008) El Sawy et al. (2010) Kim et al. (2011) Singh et al. (2011)

Table 10 continued

Item	Statement questionnaire	Sources for direct and indirect support
AOA4	Alignment of projects and initiatives with the overall strategy of the organization and top management support in order to integrate existing technologies with BI and adopt new technologies to BI are important for organizations in general Alignment of projects and initiatives with the overall strategy of the organization and top management support in order to integrate existing technologies with BI and adopt new technologies to BI are sufficient in our (client's) organization	El Sawy et al. (2010) Drnevich and Croson (2013) Daniel et al. (2014)
N/A (free text box)	Is there anything you would like to add concerning the use and adoption of assets?	
Market understanding and intimacy with BI		
MUIG1	The capability to understand market situations and create sustainable market insights and intimacy to operate in today's business environments is important for organizations in general The capability to understand market situations and create sustainable market insights and intimacy to operate in today's business environments is sufficient in our (client's) organization	For validation purposes
MUIG2	The capability to use and integrate BI to understand market situations and create sustainable market insights and intimacy to operate in today's business environments is important for organizations in general The capability to use and integrate BI to understand market situations and create sustainable market insights and intimacy to operate in today's business environments is sufficient in our (client's) organization	
MUI1	In order to measure the performance of an organization, BI is useful for organizations in general In order to measure the performance of an organization, BI is adequately used in our (client's) organization	Porter (1979) Pavlou and El Sawy (2006) Porter (2008) Roberts and Grover (2012) Drnevich and Croson (2013) Nucleus Research (2014)
MUI2	In order to gain knowledge about customers, BI is useful for organizations in general In order to gain knowledge about customers, BI is adequately used in our (client's) organization	Porter (1979) Banker et al. (2006) Pavlou and El Sawy (2006) Butler and Murphy (2008) Porter (2008) Roberts and Grover (2012) Drnevich and Croson (2013)

Table 10 continued

Item	Statement questionnaire	Sources for direct and indirect support
MUI3	In order to gain knowledge about suppliers, BI is useful for organizations in general In order to gain knowledge about suppliers, BI is adequately used in our (client's) organization	Porter (1979) Porter (2008) Banker et al. (2006) Butler and Murphy (2008) Porter (2008) Roberts and Grover (2012) Drnevich and Croson (2013)
MUI4	In order to gain knowledge about competitors or their products/services, BI is useful for organizations in general In order to gain knowledge about competitors or their products/services, BI is adequately used in our (client's) organization	Porter (1979) Banker et al. (2006) Pavlou and El Sawy (2006) Porter (2008) Roberts and Grover (2012) Drnevich and Croson (2013)
MUI5	In order to gain knowledge about an organization's own products/services, BI is useful for organizations in general In order to gain knowledge about an organization's own products/services, BI is adequately used in our (client's) organization	Porter (1979) Banker et al. (2006) Pavlou and El Sawy (2006) Butler and Murphy (2008) Porter (2008) Roberts and Grover (2012) Drnevich and Croson (2013)
MUI6	Corresponding organizational structures and coordination skills to gain data-driven market insights and achieve market intimacy with BI are important for organizations in general Corresponding organizational structures and coordination skills to gain data-driven market insights and achieve market intimacy with BI are sufficient in our (client's) organization	Pavlou and El Sawy (2006) Butler and Murphy (2008) El Sawy et al. (2010) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012) Drnevich and Croson (2013)
N/A (free text box)	Is there anything you would like to add concerning the aspect of market understanding and intimacy?	
Business operations with BI		
BOG1	The capability to achieve business operational excellence to operate in today's business environments is important for organizations in general The capability to achieve business operational excellence to operate in today's business environments is sufficient in our (client's) organization	For validation purposes

Table 10 continued

Item	Statement questionnaire	Sources for direct and indirect support
BOG2	The capability to use and integrate BI to achieve business operational excellence to operate in today's business environments is important for organizations in general The capability to use and integrate BI to achieve business operational excellence to operate in today's business environments is sufficient in our (client's) organization	
BO1	In order to achieve transparency by information gathering and preparation of decisions, the use and integration of BI is important for organizations in general In order to achieve transparency by information gathering and preparation of decisions, the use and integration of BI is sufficient in our (client's) organization	Simon (1977) Kim et al. Singh et al. (2011) (2011) Roberts and Grover (2012) Daniel et al. (2014)
BO2	Decision-making based on insights gained by BI and measuring the effect and performance of the caused actions is important for organizations in general Decision-making based on insights gained by BI and measuring the effect and performance of the caused actions is sufficient in our (client's) organization	Simon (1977) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012) Drnevich and Croson (2013) Daniel et al. (2014)
BO3	The capability to achieve business operational excellence to operate in today's business environments is important for organizations in general The capability to achieve business operational excellence to operate in today's business environments is sufficient in our (client's) organization	Banker et al. (2006) Marjanovic (2007) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012)
BO4	The capability to use and integrate BI to achieve business operational excellence to operate in today's business environments is important for organizations in general The capability to use and integrate BI to achieve business operational excellence to operate in today's business environments is sufficient in our (client's) organization	Banker et al. (2006) Marjanovic (2007) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012) Drnevich and Croson (2013)
BO5	In order to achieve transparency by information gathering and preparation of decisions, the use and integration of BI is important for organizations in general In order to achieve transparency by information gathering and preparation of decisions, the use and integration of BI is sufficient in our (client's) organization	Banker et al. (2006) Marjanovic (2007) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012)

Table 10 continued

Item	Statement questionnaire	Sources for direct and indirect support
BO6	Decision-making based on insights gained by BI and measuring the effect and performance of the caused actions is important for organizations in general Decision-making based on insights gained by BI and measuring the effect and performance of the caused actions is sufficient in our (client's) organization	Pavlou and El Sawy (2006) Butler and Murphy (2008) El Sawy et al. (2010) Kim et al. (2011) Singh et al. (2011) Roberts and Grover (2012) Drnevich and Croson (2013)
N/A (free text box)	The capability to achieve business operational excellence to operate in today's business environments is important for organizations in general The capability to achieve business operational excellence to operate in today's business environments is sufficient in our (client's) organization	
BI agility		
BIAG1	In order to operate in today's business environments, agility is important for organizations in general In order to operate in today's business environments, agility is sufficient in our (client's) organization	For validation purposes
BIAG2	In order to operate in today's business environments, agility of BI is important for organizations in general In order to operate in today's business environments, agility of BI is sufficient in our (client's) organization	
BIA1	That BI is able to cope with changes is important for organizations in general That BI is able to cope with changes is true for our (client's) organization	Knabke and Olbrich (2013) Conboy and Fitzgerald (2004) Erickson et al. (2005) Dove (2005) Galliers (2007) Rouse (2007) Pankaj et al. (2009) Conboy (2009) Caruso (2011) Evelson (2011) Poonacha and Bhattacharya (2012) Zimmer et al. (2012)
BIA2	That BI gains perceived value for (internal or external) customers is important for organizations in general That BI gains perceived value for (internal or external) customers is true for our (client's) organization	Knabke and Olbrich (2013) Conboy and Fitzgerald (2004) Erickson et al. (2005) Conboy (2009)

Table 10 continued

Item	Statement questionnaire	Sources for direct and indirect support
BIA3	That BI is able to absorb changes in an adequate time frame is important for organizations in general That BI is able to absorb changes in an adequate time frame is true for our (client's) organization	Knabke and Olbrich (2013) Conboy and Fitzgerald (2004) Erickson et al. (2005) Galliers (2007) Rouse (2007) Pankaj et al. (2009) Conboy (2009) Caruso (2011) Evelson (2011) Zimmer et al. (2012)
BIA4	That BI is able to adequately sense, diagnose and respond to change is important for organizations in general That BI is able to adequately sense, diagnose and respond to change is true for our (client's) organization	Knabke and Olbrich (2013) Galliers (2007) Rouse (2007) Pankaj et al. (2009) Evelson (2011)
BIA5	That BI is operated with an adequate architecture, data model and infrastructure is important for organizations in general That BI is operated with an adequate architecture, data model and infrastructure is true for our (client's) organization	Knabke and Olbrich (2013) Kim et al. (2011) Dove (2005) Conboy (2009) Caruso (2011)
BIA6	That BI facilitates the business model of an organization is important for organizations in general That BI facilitates the business model of an organization is true for our (client's) organization	Rouse (2007)
N/A (free text box)	Your answer to this question is very important for understanding impact factors of BI agility. In your perception, what are the main drivers of BI agility?	
N/A (free text box)	What prevents organizations from achieving BI agility?	
N/A (free text box)	Is there anything you would like to add concerning BI agility?	

Appendix B: Survey statistics

Table 11 illustrates the work experience of the participants. Fifty-three percent have more than 10 years of work experience. Further information about the participants, such as industries or consultant rate, is shown in Table 12.

Table 11 Work experience of participants

Work experience	Number	Percentage
1–2 years	2	2
3–5 years	20	18
6–10 years	30	27
11–15 years	24	22
>15 years	34	31
Total	110	100

Table 12 Industry and consultant distribution of participants

Industry	Number	Percentage (rounded)	Thereof consultants	Percentage (rounded)
Automotive	14	13	12	11
Chemicals and Pharmaceuticals	12	11	8	7
Construction	1	1	1	1
Education and Science	3	3	0	0
Finance and Insurance	24	22	23	21
Government and Public Administration	2	2	1	1
Health Services	1	1	1	1
Information and Communication	7	6	5	5
Manufacturing, Engineering or Industrial Design	4	4	3	3
Nonprofit	1	1	1	1
Process Industry	2	2	2	2
Retail and Wholesale	17	15	10	9
Transportation, Logistics and Warehousing	4	4	2	2
Utilities	5	5	4	4
Other	13	12	12	11
Total	110	100	85	77

Appendix C: Common method bias

Common method bias (CMB) is a potential problem in survey research. It exists if a significant amount of spurious variance is attributed to the measurement or data collection method rather than to the constructs that the measures represent. Ex-post statistical analysis, e.g., correlation analysis, helps to identify common method variance in the collected data (Chen and Siau 2012; Urbach and Ahlemann 2010; Podsakoff et al. 2003).

According to Pavlou et al. (2007), Chen and Siau (2012) and Bagozzi et al. (1991) correlation analysis is a useful means to determine common method bias. A high correlation among the main constructs of a model of 0.9 and above (Pavlou et al. 2007; Chen and Siau 2012) indicates the evidence of common method bias. The highest correlation among the constructs in this study is 0.73 for the general view (see Table 13) and 0.83 for the organization-specific implementations (see Table 14). This suggests that no common method bias exists. The sample size is $n = 110$.

Table 13 Correlation among main constructs (general view)

	AOA	BO	MUI	BIA
AOA	1	0	0	0
BO	0.54	1	0	0
MUI	0.55	0.73	1	0
BIA	0.45	0.72	0.64	1

Table 14 Correlation among main constructs (organization-specific implementations)

	AOA	BO	MUI	BIA
AOA	1	0	0	0
BO	0.72	1	0	0
MUI	0.71	0.83	1	0
BIA	0.72	0.83	0.74	1

Appendix D: Model validation (main study): general view

We conducted a series of tests to analyze the validation of our outer measurement model ($n = 110$).

Indicator reliability

Indicator reliability describes the extent of consistency in what an item (or a variable or a set of variables) measures and what it intends to measure. Indicator reliability can be assessed by the standardized outer loading of an item. Indicator loadings should be significant at the 0.05 level and should exceed 0.7 or 0.5 if the squared indicators are used (Urbach and Ahlemann 2010; Hair et al. 2014; Henseler et al. 2009). For exploratory research with newly developed items lower thresholds have been proposed. Hulland (1999) suggests dropping an item if the loading is below 0.4 or 0.5. But, eliminating reflective indicators has been done with care and only if the reliability of the item is low and the elimination substantially increases the composite reliability (Henseler et al. 2009). Table 15 contains the item loadings as well as the *t* values and *p* levels.

Table 15 Item loadings and cross-loadings

Latent variable	Item	*t* value	*p* level	AOA	MUI	BO	BIA
Adoption of BI assets (AOA)	AOA1	15.219	$p < 0.01$	**0.78**	0.43	0.34	0.35
	AOA2	16.491	$p < 0.01$	**0.86**	0.39	0.42	0.34
	AOA3	28.950	$p < 0.01$	**0.90**	0.56	0.50	0.46
	AOA4	19.059	$p < 0.01$	**0.79**	0.44	0.51	0.34
Market understanding and intimacy with BI (MUI)	MUI1	12.446	$p < 0.01$	0.35	**0.75**	0.56	0.51
	MUI2	26.685	$p < 0.01$	0.44	**0.84**	0.61	0.61
	MUI3	12.083	$p < 0.01$	0.49	**0.75**	0.60	0.41
	MUI4	12.896	$p < 0.01$	0.32	**0.71**	0.46	0.42
	MUI5	14.114	$p < 0.01$	0.50	**0.79**	0.55	0.51
	MUI6	16.827	$p < 0.01$	0.45	**0.81**	0.60	0.51
Business operations with BI (BO)	BO1	21.761	$p < 0.01$	0.46	0.59	**0.86**	0.62
	BO2	18.839	$p < 0.01$	0.53	0.52	**0.81**	0.51
	BO3	17.234	$p < 0.01$	0.32	0.52	**0.77**	0.51
	BO4	17.141	$p < 0.01$	0.53	0.61	**0.84**	0.56
	BO5	13.715	$p < 0.01$	0.35	0.58	**0.75**	0.60
	BO6	30.195	$p < 0.01$	0.44	0.72	**0.86**	0.70
BI agility (BIA)	BIA1	16.001	$p < 0.01$	0.36	0.47	0.60	**0.81**
	BIA2	13.447	$p < 0.01$	0.31	0.41	0.55	**0.80**
	BIA3	19.221	$p < 0.01$	0.31	0.40	0.55	**0.84**
	BIA4	14.890	$p < 0.01$	0.23	0.47	0.57	**0.81**
	BIA5	8.774	$p < 0.01$	0.42	0.63	0.54	**0.77**
	BIA6	6.905	$p < 0.01$	0.47	0.60	0.57	**0.67**

p level describes the level of significance, whereas the *t* value indicates the standardized difference between the mean of samples. Critical *t* values are 1.65, 1.96, and 2.58 for a significance level of 0.10, 0.05, and 0.01 (all two-tailed)

Internal consistency reliability

We computed two criteria to assess internal consistency reliability, Cronbach's alpha (CA) and composite reliability (CR). A high value for CA assumes that the correlation of a set of items within a construct is a good estimate for the correlation of all items within this construct (item inter-correlation) and that the items have the same meaning and range (Urbach and Ahlemann 2010; Henseler et al. 2009). CA is said to have some limitations. Therefore, we also considered composite reliability (CR) as suggested by Hair et al. (2014). Both, CA and CR should exceed the threshold of 0.7 and must not be lower than 0.6 (Urbach and Ahlemann 2010). While Nunnally and Bernstein (2010) postulate a CA of 0.95 as a desirable standard in specific cases, Straub et al. (2004) consider values above 0.95 to be suspicious. As our constructs are newly developed, we follow the threshold of 0.70 for "early stage" research of CA and CR (Nunnally and Bernstein 2010; Henseler et al. 2009). The results of the tests for internal consistency reliability are shown in Table 4.

Convergent validity

A commonly accepted criterion of convergent validity is the average variance extracted (AVE) proposed by Fornell and Larcker (1981). It measures the average amount of variance which a construct captures from its indicators in relation to the amount of measurement error. In other words, convergent validity tests whether an item measures the construct that it is supposed to measure. An AVE value of 0.5 or higher is deemed acceptable as it indicates that a construct explains more than half of the variance of its indicators (Urbach and Ahlemann 2010; Hair et al. 2014). Table 4 contains the AVE values.

Discriminant validity

Discriminant validity describes the extent to which a construct is distinct from other constructs. If discriminant validity is established, it implies that a construct is unique and items of a construct do not unintentionally measure constructs they are not supposed to measure. Discriminant validity is established to be assessed in two ways (Hair et al. 2014; Urbach and Ahlemann 2010). One way is to examine cross-loadings of indicators, and the other approach is to use the Fornell–Larcker criterion (Fornell and Larcker 1981). If cross-loadings are used, each loading of an indicator should be higher for its designated construct than for other constructs and each of the construct's highest item is among its own items compared to the corresponding constructs' items (Urbach and Ahlemann 2010). Gefen and Straub (2005) suggest 0.1 as a threshold for the difference between own loading and loadings on other constructs.

The Fornell–Larcker criterion postulates a construct to share more variance with its indicators than with other constructs. It is fulfilled if the square root of a construct's AVE is higher than the correlation with any other construct.

Recently, Henseler et al. (2015) introduced a new criterion for assessing discriminant validity, the heterotrait-monotrait (HTMT) ratio of correlations

Table 16 Discriminant validity (HTMT ratio)

Construct	Heterotrait-monotrait (HTMT) ratio			
	AOA	MUI	BO	BIA
AOA				
MUI	0.63			
BO	0.61	0.82		
BIA	0.51	0.72	0.81	

criterion. Values that meet the threshold of 0.9 are deemed acceptable (Henseler et al. 2015; Gold et al. 2001). The analysis for assessing discriminant validity with HTMT was done using SmartPLS 3 (Ringle et al. 2015).

The cross-loadings are shown in Table 15, whereas the discriminant validity check according to Fornell–Larcker is depicted in Table 4. The HTMT ratio values are shown in Table 16.

Tables 17, 18 show the path coefficients, indirect effects and the corresponding significance.

Table 17 Path coefficients and significance

Path	Path coefficient (β)	t value	p level
AOA → BIA	0.039	0.380	*ns*
AOA → BO	0.192	1.781	$p < 0.05$
AOA → MUI	0.552	6.283	$p < 0.01$
MUI → BO	0.624	7.158	$p < 0.01$
MUI → BIA	0.231	1.451	$p < 0.10$
BO → BIA	0.534	3.090	$p < 0.01$

ns not significant (one-tailed tests)

Table 18 Indirect effects and significance

Relationship	Indirect effect	t value
AOA → BO → BIA	0.103**	1.663
AOA → MUI → BIA	0.128*	1.399
AOA → MUI → BO	0.344***	5.002
MUI → BO → BIA	0.333***	2.720
AOA → MUI → BO → BIA	0.184***	2.556
AOA → BIA (sum)	0.414***	4.968

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

Appendix E: Model validation (main study): organization-specific view

Tables 19, 20, 21, 22 show the validity assessments for the second part of our study, i.e., the specific implementations of BI at the organizations ($n = 110$).

Table 19 Item loadings and cross-loadings

Latent variable	Item	t value	p level	AOA	MUI	BO	BIA
Adoption of BI assets (AOA)	AOA1	15.723	$p < 0.01$	**0.79**	0.52	0.49	0.52
	AOA2	19.754	$p < 0.01$	**0.82**	0.57	0.58	0.59
	AOA3	35.161	$p < 0.01$	**0.89**	0.62	0.64	0.63
	AOA4	39.998	$p < 0.01$	**0.88**	0.69	0.71	0.69
Market understanding and intimacy with BI (MUI)	MUI1	28.730	$p < 0.01$	0.64	**0.85**	0.71	0.56
	MUI2	17.771	$p < 0.01$	0.57	**0.82**	0.66	0.69
	MUI3	18.446	$p < 0.01$	0.52	**0.80**	0.66	0.55
	MUI4	10.082	$p < 0.01$	0.42	**0.68**	0.42	0.45
	MUI5	17.902	$p < 0.01$	0.59	**0.79**	0.69	0.56
	MUI6	31.441	$p < 0.01$	0.63	**0.85**	0.77	0.71
Business operations with BI (BO)	BO1	24.486	$p < 0.01$	0.65	0.74	**0.84**	0.69
BI agility (BIA)	BO2	25.341	$p < 0.01$	0.57	0.73	**0.85**	0.68
	BO3	24.503	$p < 0.01$	0.59	0.71	**0.82**	0.70
	BO4	38.269	$p < 0.01$	0.69	0.69	**0.89**	0.72
	BO5	14.480	$p < 0.01$	0.53	0.61	**0.80**	0.70
	BO6	25.046	$p < 0.01$	0.64	0.71	**0.88**	0.75
	BIA1	30.941	$p < 0.01$	0.68	0.70	0.77	**0.86**
	BIA2	33.300	$p < 0.01$	0.65	0.69	0.75	**0.87**
	BIA3	41.356	$p < 0.01$	0.65	0.64	0.71	**0.91**
	BIA4	27.646	$p < 0.01$	0.63	0.65	0.71	**0.86**
	BIA5	21.459	$p < 0.01$	0.56	0.55	0.67	**0.86**
	BIA6	29.459	$p < 0.01$	0.61	0.65	0.74	**0.86**

p level describes the level of significance, whereas the t value indicates the standardized difference between the mean of samples. Critical t values are 1.65, 1.96, and 2.58 for a significance level of 0.10, 0.05, and 0.01 (all two-tailed)

Table 20 Discriminant validity (HTMT ratio)

Construct	Heterotrait-monotrait (HTMT) ratio			
	AOA	MUI	BO	BIA
AOA				
MUI	0.80			
BO	0.80	0.90		
BIA	0.79	0.81	0.90	

Table 21 Path coefficients and significance

Path	Path coefficient (β)	t value	p level
AOA → BIA	0.228	2.470	$p < 0.01$
AOA → BO	0.273	2.708	$p < 0.01$
AOA → MUI	0.713	15.786	$p < 0.01$
MUI → BO	0.633	8.031	$p < 0.01$
MUI → BIA	0.088	0.928	*ns*
BO → BIA	0.595	6.901	$p < 0.01$

ns not significant (one-tailed tests)

Table 22 Indirect effects and significance

Relationship	Indirect effect	t value
AOA → BO → BIA	0.162***	2.477
AOA → MUI → BIA	0.063^{ns}	0.937
AOA → MUI → BO	0.451***	7.041
MUI → BO → BIA	0.376***	5.078
AOA → MUI → BO → BIA	0.269***	4.716
AOA → BIA (sum)	0.494***	7.595

ns not significant

*** Significant at $p < 0.01$; ** significant at $p < 0.05$; * significant at $p < 0.1$ (one-tailed tests)

Appendix F: Model validation (main study): impact of in-memory experience

The group "non-experienced IM organizations" contains participants that work at organizations using no IM technology for BI at all. For this group ($n = 31$) we analyzed their expectation, i.e., general view (Fig. 7).

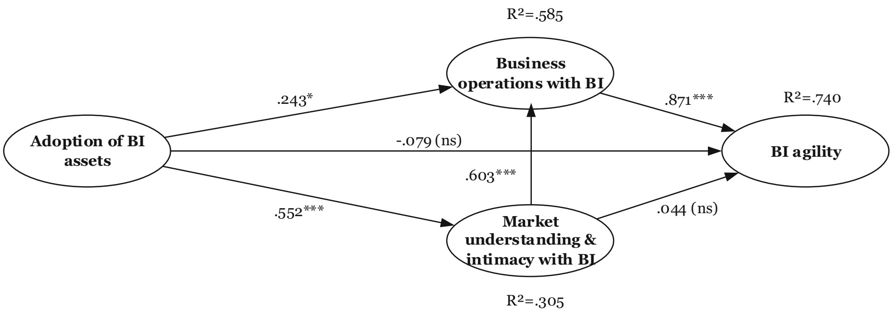

Fig. 7 Hypotheses test for non-experienced IM organizations (general view), $n = 31$. *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

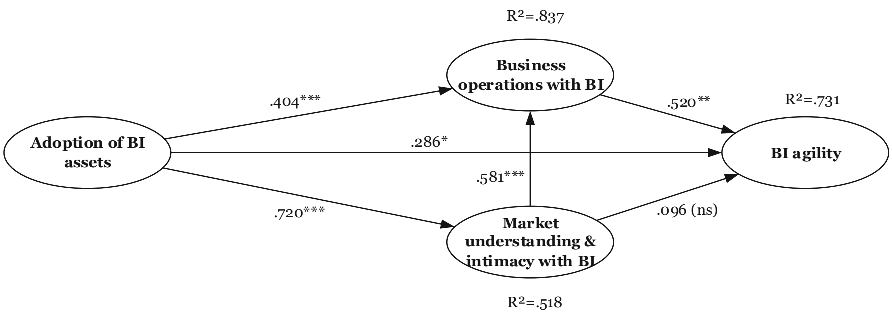

Fig. 8 Hypotheses test for experienced IM organizations (organization-specific view), $n = 39$. *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

The group "experienced IM organizations" contains participants that work at organizations that have been using IM technology for BI for at least three years. We took the organization-specific view (Fig. 8) for this group ($n = 39$).

Appendix G: Model validation (pre-study): results of scale development validation

Tables below contain the results of the outer measurement model validation of the preliminary study ($n = 16$). Tables 23 and 24 show the validation of general view, whereas Tables 25 and 26 consider the statements regarding organization-specific implementations. We assessed internal reliability using Cronbach's alpha and composite reliability (see Tables 24, 26). All values are above the proposed threshold of 0.7 for both indicators (Urbach and Ahlemann 2010). We also checked for convergent reliability with average variance extracted (AVE). Tables 24 and 26 show that the criterion is met as all values exceed 0.5 (Urbach and Ahlemann 2010). We used the Fornell–Larcker criterion to check discriminant validity. The criterion is missed in one of six cases (Tables 24, 26). Tables 23 and 25 show the item and cross-loadings.

Table 23 Items and cross-loadings (general view)

Latent variable	Item	Loading^2	AOA	MUI	BO	BIA
Adoption of BI assets (AOA)	AOA1	0.72	**0.85**	0.68	0.62	0.55
	AOA2	0.97	**0.99**	0.62	0.49	0.62
	AOA3	0.97	**0.99**	0.62	0.49	0.62
	AOA4	0.90	**0.95**	0.58	0.41	0.51
Market understanding and intimacy with BI (MUI)	MUI1	0.95	0.64	**0.97**	0.93	0.75
	MUI2	0.92	0.48	**0.96**	0.97	0.89
	MUI3	0.95	0.52	**0.97**	0.95	0.85
	MUI4	0.85	0.65	**0.92**	0.85	0.65
	MUI5	0.88	0.46	**0.94**	0.98	0.87
	MUI6	0.42	0.94	**0.64**	0.53	0.71
Business operations with BI (BO)	BO1	0.94	0.39	0.88	**0.97**	0.89
	BO2	0.94	0.40	0.90	**0.97**	0.88
	BO3	0.95	0.58	0.96	**0.97**	0.83
	BO4	0.98	0.51	0.94	**0.99**	0.88
	BO5	0.94	0.42	0.92	**0.97**	0.91
	BO6	0.74	0.81	0.94	**0.86**	0.82
BI agility (BIA)	BIA1	0.94	0.62	0.83	0.86	**0.97**
	BIA2	0.91	0.58	0.87	0.94	**0.96**
	BIA3	0.98	0.64	0.88	0.90	**0.99**
	BIA4	0.89	0.52	0.86	0.89	**0.94**
	BIA5	0.90	0.69	0.74	0.78	**0.95**
	BIA6	0.95	0.50	0.86	0.89	**0.97**

Table 24 Internal consistency and convergent reliability (general view)

	Cronbach's alpha (CA)	Composite reliability (CR)	Convergent reliability (AVE)	AOA	MUI	BO	BIA
AOA	0.96	0.97	0.89	**0.94**			
MUI	0.95	0.97	0.83	0.67	**0.91**		
BO	0.98	0.98	0.91	0.54	0.97	**0.96**	
BIA	0.99	0.99	0.93	0.61	0.87	0.91	**0.96**

The bold elements for the discriminant validity test are AVEs; squared correlations are off-diagonal

Table 25 Items and cross-loadings (organization-specific view)

Latent variable	Item	Loading^2	AOA	MUI	BO	BIA
Adoption of BI assets (AOA)	AOA1	0.89	**0.94**	0.80	0.80	0.71
	AOA2	0.93	**0.96**	0.89	0.87	0.87
	AOA3	0.82	**0.91**	0.81	0.82	0.68
	AOA4	0.86	**0.93**	0.88	0.88	0.84
Market understanding and intimacy with BI (MUI)	MUI1	0.81	0.90	**0.90**	0.87	0.85
	MUI2	0.98	0.88	**0.99**	0.97	0.77
	MUI3	0.91	0.84	**0.95**	0.97	0.69
	MUI4	0.80	0.71	**0.89**	0.92	0.55
	MUI5	0.80	0.86	**0.90**	0.87	0.57
	MUI6	0.93	0.88	**0.96**	0.96	0.77
Business operations with BI (BO)	BO1	0.89	0.83	0.95	**0.94**	0.74
	BO2	0.90	0.84	0.96	**0.95**	0.56
	BO3	0.88	0.94	0.92	**0.94**	0.76
	BO4	0.96	0.88	0.98	**0.98**	0.73
	BO5	0.86	0.81	0.92	**0.93**	0.75
	BO6	0.84	0.81	0.90	**0.92**	0.78
BI agility (BIA)	BIA1	0.92	0.78	0.73	0.73	**0.96**
	BIA2	0.92	0.82	0.72	0.71	**0.96**
	BIA3	0.88	0.71	0.66	0.70	**0.94**
	BIA4	0.93	0.78	0.72	0.74	**0.96**
	BIA5	0.91	0.86	0.77	0.79	**0.95**
	BIA6	0.92	0.82	0.72	0.71	**0.96**

Table 26 Internal consistency and convergent reliability (organization-specific view)

	Cronbach's alpha (CA)	Composite reliability (CR)	Convergent reliability (AVE)	AOA	MUI	BO	BIA
AOA	0.95	0.97	0.87	**0.94**			
MUI	0.97	0.98	0.87	0.91	**0.93**		
BO	0.97	0.98	0.89	0.90	0.99	**0.94**	
BIA	0.98	0.98	0.91	0.83	0.76	0.77	**0.96**

The bold elements for the discriminant validity test are AVEs; squared correlations are off-diagonal

Appendix H: Control variable: size of organization

We assessed the robustness of the research model by using the size of organization, i.e., the number of employees, as control variable (n = 110). This analysis is shown in Table 27 and Fig. 9 (general view) and Table 28 and Fig. 10 (organization-specific view).

Table 27 Path coefficients and significance incl. control variable (general view)

Path	Path coefficient (β)	t value	p level
AOA → BIA	0.040	0.413	*ns*
AOA → BO	0.192	1.787	$p < 0.05$
AOA → MUI	0.552	6.393	$p < 0.01$
MUI → BO	0.624	3.029	$p < 0.01$
MUI → BIA	0.236	1.499	$p < 0.1$
BO → BIA	0.524	3.029	$p < 0.01$
ORG → BIA	0.103	1.411	$p < 0.1$

ns not significant (one-tailed tests)

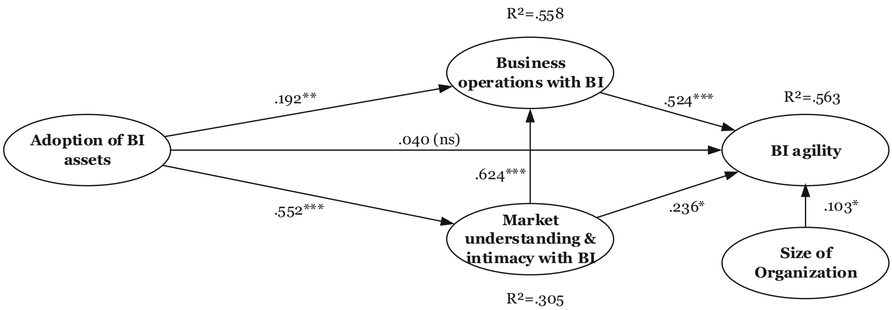

Fig. 9 Hypotheses test incl. control variable (general view). *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

Table 28 Path coefficients and significance incl. control variable (organization-specific view)

Path	Path coefficient (β)	t value	p level
AOA → BIA	0.220	2.380	$p < 0.01$
AOA → BO	0.273	2.669	$p < 0.01$
AOA → MUI	0.713	15.818	$p < 0.01$
MUI → BO	0.633	6.911	$p < 0.01$
MUI → BIA	0.088	0.934	*ns*
BO → BIA	0.596	6.911	$p < 0.01$
ORG → BIA	−0.049	0.974	*ns*

ns not significant (one-tailed tests)

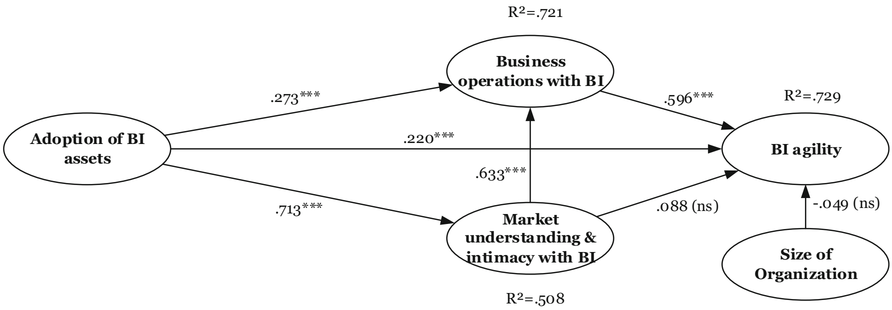

Fig. 10 Hypotheses test incl. control variable (organization-specific view). *ns* not significant; ***significant at $p < 0.01$; **significant at $p < 0.05$; *significant at $p < 0.1$ (one-tailed tests)

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