ISSN 1822-8038 (online)
INTELEKTINĖ EKONOMIKA
INTELLECTUAL ECONOMICS
2022 , No 16(1), p. 5-23

BUILDING A CONCEPTUAL FRAMEWORK FOR USING BIG DATA ANALYTICS IN THE BANKING SECTOR

Mr. Dai Thich Phan[1]

Hantos Elemér Doctoral School of Business, Management and Regional Sciences, Faculty of Economics, University of Miskolc, Hungary
Email: sttpd@uni-miskolc.hu
Mail address: Room 219, A4 Building, Egyetem Varos 3515, Miskolc, Hungary

Mrs. Lam Quynh Trang Tran

Károly Ihrig Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Hungary
Email: lam.tran@econ.unideb.hu

DOI: 10.13165/IE-22-16-1-01

Abstract. *Big Data and Big Data Analytics (BDA) are becoming trending technologies of the future. This topic has garnered considerable interest from researchers and businesses. However, BDA research in the banking sector has proven to be extremely limited and mixed. Addressing the challenges of BDA application and laying the foundation for BDA to improve banking efficiency raises significant questions about strategic management in the banking sector. Through a systematic review of the literature and a case study in Hungarian banks, this study intends to address the major inconsistencies in existing ideas about BDA applications. This study also proposes a conceptual model to evaluate the impact of factors influencing the use of BDA in the banking sector and investigates whether BDA affects the performance of banks. Our study finds that the use of BDA in the banking sector has to be aligned with the creation of dynamic capabilities that positively and directly affect banking in terms of the market and operational performance. Meanwhile, the dynamic capabilities created by BDA usage have a moderating impact on bank performance through improved risk management performance. Furthermore, this research helps managers focus on key factors, namely technological infrastructures, Big Data skills, data quality, and top management support, to boost the efficiency of using BDA.*

Keywords: *Big Data analytics; banking efficiency; risk management*

JEL index*: G21; O33*

[1] Corresponding author

1. Introduction

Big Data is among the emerging technologies that national digital strategies target (OECD, 2015). For example, France invested EUR 150 million to support R&D in BDA and four other strategic digital technologies. Meanwhile, Germany has established two Big Data solution centers to boost Big Data applications in industrial applications, life sciences, and the healthcare sector (OECD, 2015). As one of the growing trends in the Industry 4.0 era that has revolutionized business management (Raguseo & Vitari, 2018), Big Data is becoming an increasingly prominent topic of research and is considered a revolutionary change in many industries (Wamba et al., 2017). Big Data is an important driving force for supply chain management and directly influences firms' business growth, especially in highly dynamic markets (Chen et al., 2015). Big Data can offer endless insights and valuable information to enhance the transformation process of firms that adopt it (Mikalef & Krogstie, 2020). Small and medium-sized enterprises (SMEs) use BDA to create business value in terms of strategic value, transactional value, transformational value, and informational value, which have a positive impact on the company's market performance and financial performance (Maroufkhani, Tseng et al., 2020).

The Big Data story far exceeds the limits of information technology (Braganza et al., 2017). Implementing Big Data initiatives would inevitably entail factors that are required to achieve its benefits; not simply buying a computer device. Successful businesses rarely improve their performance solely through the use of new technologies (Popovič et al., 2018). To be successful with BDA solutions, organizations must carefully consider technical factors and all relevant aspects related to strategic management, human resources, corporate culture, and government policies (Raguseo & Vitari, 2018). According to Maroufkhani and Tseng et al. (2020), SMEs need to focus on technological, organizational, and external support issues to successfully implement BDA. Meanwhile, for logistics firms, perceptions of the benefits of BDA and top-level management support greatly influence whether or not BDA is used (Lai, Sun & Ren, 2018). Consequently, to provide organizations with the effectiveness and competitive advantage of Big Data solutions, the planning and development of Big Data initiatives must provide business value such as strategic value, transactional value, transformational value, and informational value. Additionally, investing in BDA solutions is considered risky and expensive (Mikalef & Krogstie, 2020; Raguseo & Vitari, 2018); it also comes up against barriers during implementation. Alharthi, Krotov, and Bowman (2020) recognized the importance of removing barriers to achieve optimal results when using BDA. These barriers arise from technical barriers such as infrastructure readiness, data complexity, human barriers such as lack of skills, and organizational barriers such as confidentiality and organizational culture.

From an academic point of view, most of the research on BDA has been done in the fields of marketing (Erevelles et al., 2016), tourism (Miah et al., 2017), transportation (Zhu et al., 2018), smart cities (Ghani et al., 2019), healthcare (Wang & Hajli, 2017), and social media (Ghani et al., 2019). Unfortunately, research on the banking industry has been mostly restricted to BDA benefits by analyzing the best practices of BDAs among banks (Hung, He & Shen, 2020; Shakya & Smys, 2021; Srivastava & Gopalkrishnan, 2015; Sun et al., 2014) and literature reviews (Nobanee et al., 2021). Despite the importance of BDA in the banking industry and the high cost of infrastructure investment for BDA (Mikalef & Krogstie, 2020), there remains a paucity of evidence on the significant factors influencing the successful use of BDA. Moreover, although commercial reports say a lot about the applications and effectiveness of BDA, little detailed investigation into how to build an implementation framework which leads to effective and efficient results from the use of BDA at banking institutions exists.

This research aims to answer the following research question: How can the benefits of BDA usage in the banking sector be boosted?

In order to answer the study question, a systematic literature review is utilized, integrating practical evidence from the banking sector to establish a conceptual model of the usage of BDA. This study aims to contribute to this growing area of research by clarifying the current contentions among researchers regarding Big Data resources and building a conceptual framework for using BDA in banking sectors through a combination of dynamic capability and the Technology-Organization-Environment (TOE) framework. Furthermore, this study describes the current situation of BDA in a European country.

This study is organized in the following way. The second part presents an overview of Big Data and BDA, practical applications of BDA in various industries, and related theories and research on the use of BDA at the organizational level. The third part is concerned with the systematic literature review method used for this study. Part four presents the conceptual framework, focusing on the combination of the TOE framework and dynamic capabilities theory. The final part is the conclusion, which provides the theoretical and practical contribution, limitations, and future directions.

2. Literature review

2.1. Big Data and BDA

Every day, a huge amount of data is created around the world. For example, Facebook creates around 500 terabytes of log data every day, Walmart uploads one million new customer transactions per hour, and Youtube uploads around 100 hours of video each minute (Kambatla et al., 2014). These figures reveal that larger and more diverse datasets, such as structural data (text, numeric), semi-structural data (voice, video, image), or nonstructural data (social tweets, comments), will be increasingly generated. There is no generally established definition of Big Data, but Big Data has become an attractive term in academia (Zhou et al., 2014). Therefore, researchers quite often come across new definitions of Big Data. Most studies acknowledge that the first definition of Big Data is from Laney (2001), who observed that Big Data implies data sets with the "3V" characteristics: volume, velocity, and variety. These characteristics make data governance exceed the limits of existing technology (Dumbill, 2013). Under a working definition from HMG (2014), Big Data refers to a large amount of complex data which requires more advanced analytical techniques to obtain meaningful insights from in real-time (HMG 2014). Likewise, the European Commission (2018) considers data to be Big Data if it has four characteristics: a large amount, different types, high velocity, and various sources. Over time, the 3V concept was gradually added to with another V, depending on each author's point of view (Wang, 2012). For instance, besides the generally accepted 3V characteristics of Big Data – volume, velocity, and variety – Zhou et al. (2014) added a new characteristic: veracity. Through a literature review, Sivarajah et al. (2017) even identified the 7V characteristics of Big Data: volume, variety, veracity, value, velocity, visualization, and variability.

From a managerial point of view, Big Data is increasingly being recognized as raw material in business operations. According to Fosso et al. (2015), Big Data's ultimate goal is to deliver business value and create a competitive advantage. For managers in large firms, the most impressive thing about Big Data is the opportunities and benefits that Big Data brings, and the infrastructure requirements (Schultz, 2013). This idea suggests an urgent need for a more in-depth understanding of how to use BDA effectively and what factors would play a key role in this process.

2.2. Studies in BDA at the firm level

Factors affecting BDA adoption/usage.

Previous research has established that different variables are related to the adoption/usage of BDA at the firm level (Table 1). By adopting the TOE framework, many recent studies (e.g., Chen et al., 2015; Maroufkhani, Wan Ismail & Ghobakhloo, 2020) have shown that technological, organizational, and environmental factors can play a key role in affecting the adoption of BDA at large or SME enterprises. However, these factors can vary depending on the type of industry or organization (Sun et al., 2018). Moreover, Verma and Chaurasia (2019) found considerable differences among adopters and non-adopters regarding how firms decide to use BDA. For adopters, technological factors (relative advantage, complexity), organizational factors (top-level management support, technology readiness, organizational data environment), and the environmental factor (competitive pressure) become more important in adopting BDA; meanwhile, for non-adopters, the significant factors are relative advantage, complexity, and competitive pressure. The factors affecting BDA usage/adoption require more research, as differences exist between sectors and countries (Maroufkhani, Wan Ismail & Ghobakhloo, 2020; Raguseo & Vitari, 2018; Sun et al., 2018).

Table 1: *Recent studies in factors influencing the use of BDA*

Authors	Country	Direct Factors (adoption intention/ actual usage)
(Chen et al., 2015)	161 firms worldwide	Expected benefits, technological compatibility, top-level management support
(Sun et al., 2018)	Not given	Twenty-six identified factors influence the adoption of business intelligence and analytics
(Gangwar, 2018)	478 firms India	Relative advantage, compatibility, complexity, top-level management support, organizational size, competitive pressure, vendor support, data management, data privacy
(Lai, Sun & Ren, 2018)	210 firms in China	Perceived benefits, top-level management support
(Park & Kim, 2019)	Korean firms	The strongest determinants of adoption are: the benefits from Big Data, technological capabilities, financial investment competence, and data quality and integration

(Verma & Chaurasia, 2019)	Indian firms	The relative advantage, complexity, compatibility, top-level management support, technology readiness, organizational data environment, and competitive pressure (for adopters)
(Maroufkhani, Wan Ismail & Ghobakhloo, 2020)	112 SMEs in Iran in the manufacturing sector.	Technology and organizational factors are the most influential in BDA adoption

The use of BDA in firms

The benefits brought from BDA have been witnessed in many areas, such as the finance and banking sector, supply chain, health care, and sport (Ali et al., 2020; Hung, He & Shen, 2020; Troilo et al., 2016). BDA benefits both incumbent firms and start-up firms. While traditional firms could use BDA to capture new opportunities, improve products and services, and enhance operations, they could also deliver new products and services, creating new business models through BDA (Hung, He & Shen, 2020). In addition, BDA could bring SMEs comprehensive insights, enable faster and more accurately decision-making, and reduce operational cost (Maroufkhani, Tseng, et al., 2020). The applications and features that BDA offers vary from sector to sector. For example, administrators can improve public transit efficiency in the transportation sector in terms of traffic scheduling, planning, or scheduling optimization based on data analysis obtained from Taxi trip data, GPS, GIS and mobile phone data, sensors, and web data (Welch and Widita, 2019). For the healthcare sector, data can come from clinical data, biometric data, financial data, or data from social media, which are then processed and analyzed for diagnostics, telemedicine, patient treatment, or personalized medicine (Batko and Ślęzak, 2022).

BDA and banking research

Banks are one of the domains that are valued as early IT adopters in data-driven decision-making (Hung, He & Shen, 2020). Storing large amounts of customer data about interaction channels is a major competitive advantage for banks (Hung, He & Shen, 2020). In the age of Big Data, there are three recognizable trends in the application of BDA in banks. Firstly, by using large volumes of data on demographics, financial situations, transaction behaviors based on over-the-counter transaction channels, ATMs, mobile apps, internet channels, and social media, banks can better understand customer behavior, thereby improving the effectiveness of marketing activities (Ali, 2020; Hung, He & Shen, 2020). From a customer perspective, Giebe, Hammerström, and Zwerenz (2019) suggest that using BDA can increase customer loyalty through customer advisory services. Second, banks are using Big Data in volume, velocity, and variety to detect fraud and manage risk more accurately (Shakya & Smys, 2021; Srivastava & Gopalkrishnan, 2015). Third, compared to traditional data analysis, BDA allows banks to process large amounts of data faster (Sun et al., 2014), which contributes to improving their efficiency. Unfortunately, however, research on Big Data in the banking sector is still rather modest.

BDA is among the leading future technologies (Morabito, 2014); however, the popularity of BDA in Hungary is still lagging behind other countries (Kő, Fehér & Szabó, 2019). For an in-depth understanding of the usage of BDA in the Hungarian banking sector, we conducted a survey in December 2021 with the assistance of the Hungarian Banking Association. Primary inclusion criteria for selecting participants were at least five years of experience in digital transformation and Big Data projects related to banking sectors. Among these fourteen experts, there were three researchers from universities and fintech centers, one data analytics consultant, one manager at the Hungarian central bank, and nine high and medium-level managers at banks in Hungary. As a result, opinions from these experts provided us with high reliability and validity of evidence. The first question elicited information on the importance of BDA, and this survey among experts in the Hungarian Banking sector confirms that BDA plays a particularly significant role in the banking industry. Almost 50% of respondents agreed that banks might use BDA in the future; meanwhile, more than 40% said that banks are using BDA in some functional departments, while just one bank manager said they were testing BDA projects. In terms of the cost benefits, half of the respondents indicated that there is no cost reduction, or none that may be demonstrated yet, with BDA projects. However, more than 30% agreed that banks could achieve up to 10% cost reduction. Notably, one respondent who works on the board of directors in a large bank agreed that their bank could achieve around 40% cost reduction with BDA solutions. More than 50% of respondents indicated that risk management, fraud and crime prevention, sales and marketing, customer relations, and customer experiences are the most adopted departments in banks. Data quality, top-level management support, and BDA skills are the most critical factors influencing the success of BDA implementation (Figure 1). All respondents agreed that BDA skills combine IT skills, data science skills, and business skills. Among them, programming and problem-solving skills are the most important skills for BDA.

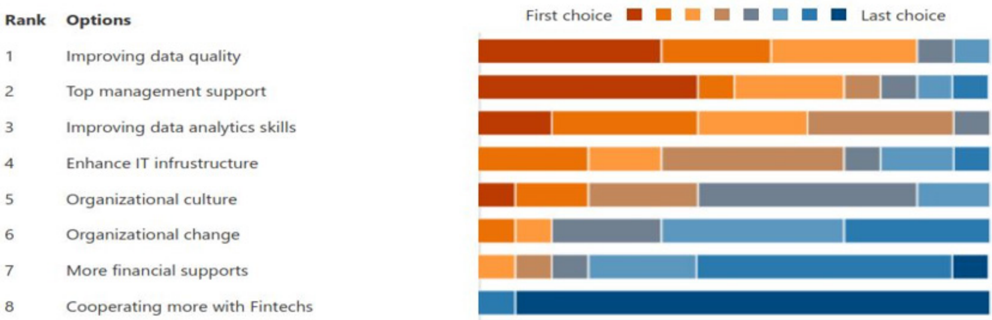

Figure 1: *The ranking of significant factors in the successful use of BDA at banks*
Source: *Authors' elaboration*

3. Methodology

This study uses a systematic literature review to gain insights into the adoption and use of BDA among enterprises. Firstly, the authors searched for relevant studies using Scopus and Web of Science, two of the most comprehensive databases in this field. Next, keywords related to our topic were applied, such as Big Data and BDA, combined with use, usage, adopt, and adoption in the field of banking or finance. Criteria for selecting publications were as follows: (1) publication in journals; (2) language in English.

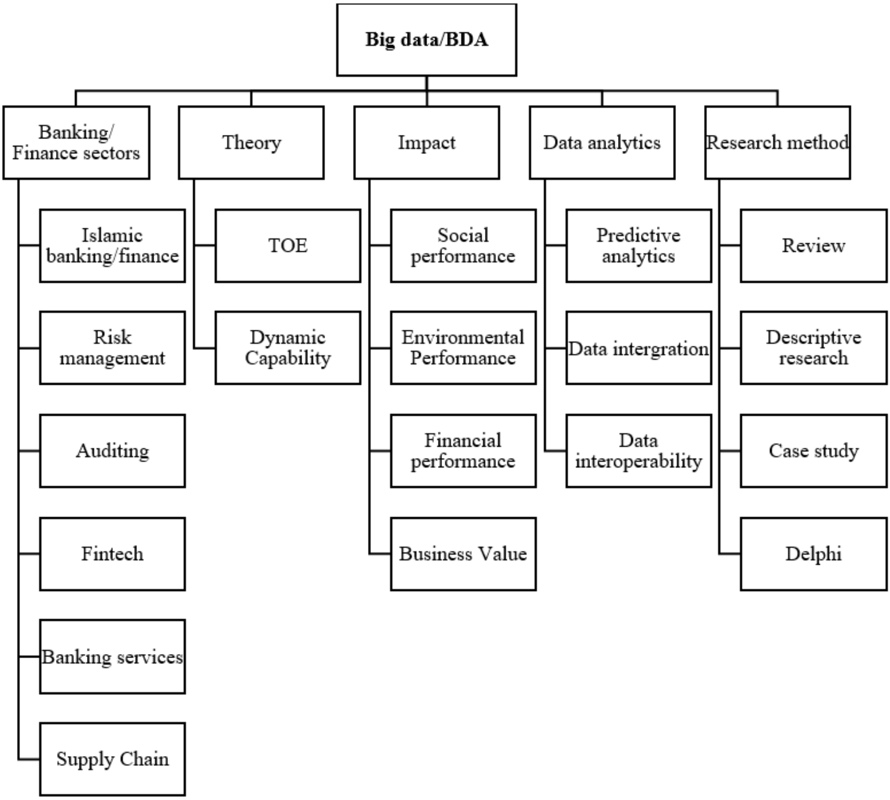

Figure 2: *The main themes from BDA studies in the banking sector*
Source: *Keywords collected from Scopus/ the Web of Science*

The authors found 20 studies in SCOPUS and 20 studies from the Web of Science database. For the purpose of analysis, abstract reviews were conducted, after which only 12 studies were included in the following part. Figure 2 demonstrates that previous studies mostly use the case study and review method to describe the application of BDA in the banking sector. Among the most common functions mentioned in previous studies are risk management, Islamic banking, banking services, and supply chain finance. Research regarding the use of BDA in banks is very limited. Therefore, article references were searched further for additional relevant publications on Google Scholar.

4. Conceptual framework

The development of the research model

A conceptual framework was created to explain how classic theory has advanced current research. Ravitch and Riggan (2016) suggest that conceptual frameworks should explain why and how important topics should be studied. An effective conceptual framework should convince future researchers of the importance of research by suggesting and highlighting the most important features of relationships and data (Ravitch & Riggan, 2016). Jabareen (2009) argues that conceptual frameworks should generate coherent new interpretations within a particular field of study.

This part of the study aims to explain how the conceptual framework has evolved. The resource-based view (RBV) is among the most common and effective theories for studying the impact of information technology on performance. Barney (2014) explained that the firm's performance depends on the characteristics/quality of its resources and capabilities. Barney (1991) also presented a classification of firms' resources, including physical capital resources, human capital resources, and organizational capital resources. Theoretically, firms use strategic resources that are valuable, rare, inimitable, and non-substitutable (VRIN) to create sustainable competitive advantage (Barney, 1991; Eisenhardt & Martin, 2000). To evaluate the impact of BDA on firm performance, some authors have relied on the resource-based view theory. According to Gunasekaran et al. (2017), BDA assimilation is considered a capability that provides a competitive advantage for organizations in terms of operating performance and supply chain performance. This view is supported by Maroufkhani, Wan Ismail, and Ghobakhloo (2020), who found that BDA adoption functions as a form of knowledge capability and an intangible resource for firms to enhance their performance. In terms of creating business value from BDA, Raguseo and Vitari (2018) acknowledge that a BDA solution brings higher business value and higher competitive advantage. Meanwhile, Müller, Fay and vom Brocke (2018) suggest that by using BDA as an asset, firms can improve their productivity by around 3–7%. Drawing on RBV, Wamba et al. (2017) confirm that BDA capability is the critical organizational capability to provide a sustainable competitive advantage. Built from three sub-IT capabilities, BDA capability delivers a direct positive impact on business processes and firm performance.

However, researchers also pointed out the two biggest limitations when applying RBV in research on Big Data initiatives. First, RBV fails to address the influence of market dynamism and firm evolution over time (Wang & Ahmed, 2007). Second, data is considered the core resource in Big Data solutions, but data access and use by many parties is now possible (Braganza et al., 2017). Braganza et al. (2017) concluded that under the analytical lens of RBV, the core resource in Big Data initiatives is data, which does not satisfy the rarity characteristic. The authors argue that, in Big Data initiatives and projects, data can be obtained by third parties, vendors are also ready to provide Big Data solutions to buyers when a business uses BDA, and competitors also have BDA implementation capabilities. Therefore, the influence of BDA as a core resource on sustainable competitive advantage will be reduced.

Recognizing some drawbacks of RBV, Braganza et al. (2017) called for further research on Big Data with more of a focus on dynamic capabilities theory. Dynamic capabilities theory has been extended from RBV, and has attempted to explain how firms achieve competitive advantage in dynamic markets (Eisenhardt & Martin, 2000). Dynamic capabilities are viewed as an emerging and potentially integrative approach to understanding new sources of competitive advantage

(Teece, Pisano & Shuen, 1997). RBV pays attention to resources, while dynamic capabilities emphasize organizational and strategic routines (Eisenhardt & Martin, 2000).

Wang and Ahmed (2007) refer to resources as the firm's foundation, and capabilities can deploy these resources to attain the desired goal. These resources and capabilities cannot retain or satisfy VRIN characteristics, and they cannot create competitive advantages for firms in a dynamic market environment. Wang and Ahmed (2007) noted that "dynamic capabilities emphasize a firm's constant pursuit of the renewal, reconfiguration and re-creation of resources, capabilities and core capabilities to address the environmental change." They also identified the three most important factors contributing to dynamic capabilities: adaptive capability, absorptive capability, and innovative capability; through these capabilities, a firm can "integrate, reconfigure, renew and recreate its resources and capabilities" to gather changes from external factors (Wang & Ahmed, 2007). Following this line of thought, by collecting relevant data from internal and external sources, BDA allows banks to understand their customers more deeply, therefore helping banks to follow up and perceive market/customer changes better, even in real-time. In addition, banks can make changes and upgrade their products/services to meet new customer needs while helping to improve and create more effective marketing campaigns (Mikalef & Krogstie, 2020). This means that using BDA is closely aligned with creating adaptive capability. For example, Disney uses Big Data obtained through RFID mounted on bracelets to analyze customer behavior, provide better experiences for park visitors, and improve its marketing effectiveness (Van Rijmenam, 2014). Some authors have applied dynamic capabilities theory as a foundation for Big Data research (Ali et al., 2021; Ghasemaghaei et al., 2017). By employing dynamic capabilities theory, Ghasemaghaei et al. (2017) found that data analytics work as a dynamic capability that influences the agility of enterprises.

This study uses dynamic capabilities theory as the foundation for BDA usage on firm performance, where BDA usage is conceptualized as a dynamic capability of a firm. Using BDA is considered an organizational capability because this new technology allows businesses to process and exploit their Big Data resources to sustain competitiveness, such as market performance and operational performance (Gupta et al., 2019). Some tools from using BDA among firms are considered replaceable, homogeneous, or, as far as Eisenhardt and Martin (2000) observe, as commonality. Therefore, the use of BDA across firms reflects the key characteristics of dynamic capabilities suggested by the literature: commonalities in key features, coupled with idiosyncrasy in detail (Eisenhardt & Martin, 2000; Wang & Ahmed, 2007). The common feature in using BDA across firms, for example, is successful customer intelligence. By integrating data types from structured to unstructured or using analytical tools such as data mining, firms can understand customer behavior based on customers' activity on their website and mobile apps. However, idiosyncrasy characteristics in dynamic capabilities such as BDA usage are expressed in the differences between firms in the service/product development process, the business process, and customer service. For example, even using the same BDA, each bank utilizes BDA to provide different products. Therefore, the concept of dynamic capabilities has now been greatly expanded compared to the original one. Helfat et al. (2007) emphasized dynamic capabilities associated with changes to differentiate from normal operational capabilities. Dynamic capabilities refer to "the capacity of an organization to create, extend, or modify its resource base purposefully" (Helfat et al., 2007, p. 1). The capacity to change resource bases creates many advantages for firms, such as:

creating new products, models, and production processes. Therefore, to maximize the benefits of dynamic capabilities, firms need to fully evaluate their internal and external factors (Mikalef & Krogstie, 2020). Regarding IT capabilities, Kohli and Grover (2008) advocate that IT capabilities are frequently built via means of combining specific physical/IT infrastructure with both human and organizational resources. Therefore, we assert that the dynamic capabilities resulting from the use of BDA are shaped by the combination of core resources/capabilities. Therefore, this study conceptualizes BDA usage as a competitive capability facilitated by four core resources/capabilities, such as data quality, technical infrastructure resources, management support, and data analytics skills. For these reasons, it is necessary to combine the TOE framework with dynamic capabilities when studying BDA.

Few previously published studies have combined dynamic capabilities and the TOE framework. The TOE framework was introduced in 1990 by Tornatzky and Fleischer, and has become a prominent theory in adopting information technology to explain IT adoption at the firm level (Lai, Sun & Ren, 2018). According to Tornatzky and Fleischer (1990), many factors that impact innovation adoption in firms can be grouped into three main contexts: technological, organizational, and environmental. The biggest advantage of the TOE framework is that it offers flexibility in research; researchers can remove or add related variables into their studied model depending on the specific type of technology or subject. Gupta et al. (2019) evaluated how ERP and Big Data predictive analytics impact firm performance by applying dynamic capability. Research suggests that building BDPA is influenced by three factors: data, managerial, and technical skills. Of the many factors influencing BDA use, top management support is found in most previous studies. Meanwhile, managerial and technical skills factors were suggested from studies in the banking sector (Ali et al., 2021). Our study aims to combine this key factor from previous studies with three other factors that affect BDA use: IT infrastructure readiness, BDA skills, and data quality.

Proposed research model

Based on the above argument, this part of the study explains and presents a proposed research model for BDA in the banking sector. Our model combines four important factors from the TOE framework and dynamic capabilities (Figure 3).

Prior research indicated that technological readiness, technological competence, or organizational readiness is the state of being prepared, both in terms of facilities and skills, to ensure that firms qualify when using new technologies (Maroufkhani, Wan Ismail & Ghobakhloo, 2020; Wang, Wang & Yang, 2010). In addition, for BDA, IT infrastructure provides the technical basis for the smooth implementation of Big Data initiatives (Lai, Sun & Ren, 2018; Park & Kim, 2019). Therefore, small and medium-sized enterprises need adequate technical resources, and enterprises cannot implement BDA without adequate technical resources (Maroufkhani, Wan Ismail & Ghobakhloo, 2020). Therefore, in Figure 3, our research supports the idea that IT infrastructure readiness will have a positive impact on the usage of BDA.

Data characteristics imply the size of data in terms of volume, velocity, and variety. When banks face the characteristics of Big Data, they tend to use BDA to optimize what data brings (Ghasemaghaei, 2018). In the modern world, the internet and mobile phones allow banks to interact more frequently with customers and to collect more data. These data increase volume, velocity, and variety in structural/semi-structural or unstructured formats. In addition, the development of technology and collaboration with third parties will enable banks to retrieve more data from diverse sources with different data types. Research from Lai, Sun, and Ren (2018) shows that when data becomes larger in volume, is created at higher speed, and is stored in a more diversified way, more enterprises tend to adopt BDA. However, enterprises are more concerned with data quality and Big Data integration into BDA usage (Park & Kim, 2019). Data quality refers to the consistency and integrity of the collected data (Kwon, Lee & Shin, 2014). This means that banks with higher data quality will increase their use of BDA. As a result, this study supports the idea that data quality will positively influence the usage of BDA at banks.

Implementing and maintaining complex BDA projects requires staff knowledge and skills (Ali et al., 2021; Gangwar, 2018). Grossman and Siegel (2014) observed that BDA techniques combine data analysis, business knowledge, and IT skills. BDA personnel should be capable of dealing with emerging technologies such as natural language processing, text mining, video/voice/image analytics, and visual analytics (Schultz, 2013). Park and Kim (2019) suggested that the relevant Big Data management and analytic competency can be achieved through training and external experts. Verma and Chaurasia (2019) agreed that employees or data scientists should use high-level data science practices to understand the business domain in order to comply with BDA requirements and provide actionable business outcomes. Therefore, BDA technology is one of the main factors driving enterprises to implement BDA solutions (Verma & Chaurasia, 2019). Maroufkhani, Tseng et al. (2020) also found that BDA skills play the most significant role in using BDA. Therefore, it is highly likely that BDA skills have a positive impact on the usage of BDA in the banking sector.

Liang et al. (2007) explain that the commitment of top-level management includes both the beliefs and participation of top-level managers. Top-level management's beliefs show managers' beliefs about the business benefits of IT innovation, while top-level management participation demonstrates managers' support by creating visions, strategies, goals, and standards for IT innovation. The beliefs and participation of top-level management have a significant impact on how organizations embrace IT transformations. Mikalef and Krogstie (2020) argued that it is difficult for firms to achieve higher levels of innovation capability without the support of management. Another study also confirmed the strategic importance of top-level management support for BDA use (Chen et al., 2015). When top-level managers understand the benefits of BDA, they will support the use of BDA in many forms, such as by: building infrastructure, upgrading BDA skills, and providing financial support (Lai, Sun & Ren, 2018). Using BDA requires gathering, analyzing, and understanding data from many different enterprise functions so that top-level management support will promote and solve communication and coordination problems (Chen et al., 2015; Verma & Chaurasia, 2019), reducing conflict/resistance (Gangwar, 2018). Ali et al. (2020) found that banks' commitment to Big Data had significant positive impacts on their environmental and financial performance. Meanwhile, managerial skills play a significant role in creating BDA capability at banks (Ali et al., 2021). Therefore, our study recognizes that BDA usage will be more beneficial with stronger top-level manager support.

Ghasemaghaei's (2018) study identified the benefits of BDA in providing better products/services and improving customer experience. Many large banks are using Big Data to understand customers' awareness, perceptions, and satisfaction (Schultz, 2013). For example, banks can analyze unstructured or semi-structured data and identify customer needs or concerns through website clicks or voice recordings from call centers (Schultz, 2013). A major purpose of using Big Data at the Bank of America is to improve the quality of customer information (Schultz, 2013). Through understanding more about customers, banks would be able to explore new markets more quickly, introduce new products or services into the market faster, achieve a higher success rate of new products or services, and gain more market share than their competitors. Using large volume, real-time data and different data types could help firms provide better products/services and enhance their efficiency above that of their competitors (Q. Ali et al., 2020; Ghasemaghaei, 2018). Process-level performance in the Ghasemaghaei (2018) study is consistent with the previous study from Ramanathan et al. (2017), who concluded that it is likely that business analytics has a significant impact on business performance, which is most noticeable at the process level. Like other IT solutions, Big Data can produce valuable advances in the time required to complete a computing task. For example, it is easy to see that business analytics provides more insight into customers, thereby performing more effective marketing campaigns. Likewise, a recent report from the Magyar Nemzeti Bank also points out that most financial institutions expect AI, Big Data, and cloud technology to have the most significant impact on business processes (Magyar Nemzeti Bank, 2020). Belhadi et al. (2019) argued that using BDA helps improve intra-and inter-organizational transparency and accountability, helps managers make decisions more quickly and accurately, and improves employees' efficiency. Similarly, a positive relationship between BDA usage and operational performance was found from a previous study by Gupta et al. (2019).

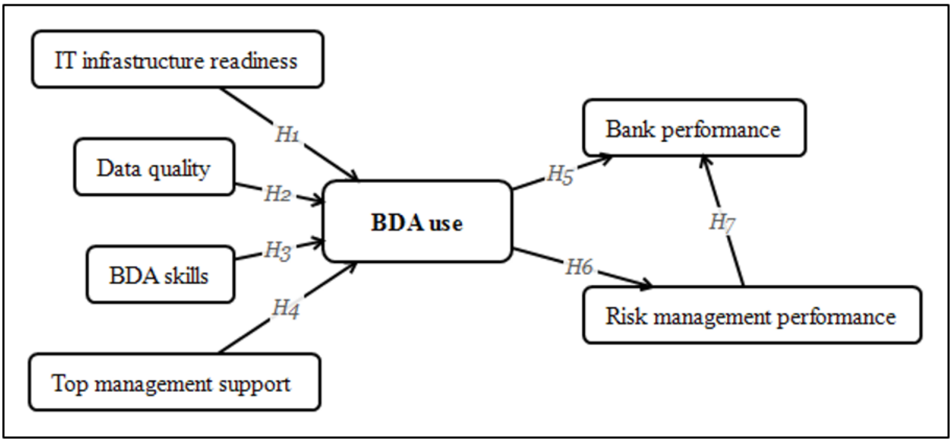

Figure 3: *Conceptual framework*

Source: *Authors' elaboration*

Risk management is one of the key functional differences between the banking industry and non-financial firms (Aebi, Sabato & Schmid, 2012). Therefore, technological innovations will influence the risk management sector in banking operations. In particular, the wave of applications for BDA technologies will benefit risk managers at banks to make smarter decisions at lower costs (Härle, Havas & Samandari, 2016). For instance, BDA analyzes customers' information to help banks make accurate decisions about the provision of services such as retail lending and financial crime detection.

Figure 3 shows that IT infrastructure readiness, BDA skills, data quality, and top-level management support are the main factors influencing BDA usage in banks (H1, H2, H3, H4). Furthermore, the usage of BDA in this model refers to the ability to create dynamic capabilities such as adaptive, absorptive, and innovative capabilities. Accordingly, the use of BDA at banks can improve banking performance in two ways. Firstly, it directly enhances the bank's performance in terms of market and operational performance (H5). Secondly, the usage of BDA at banks can improve risk management performance and subsequently help improve the bank's performance (H6, H7).

4. Conclusion

4.1. Theoretical contributions

This article aimed to theoretically study the impact of BDA on bank performance. Building on the arguments and analysis of previous studies, this study provided a deeper understanding of the factors influencing the successful use of BDA and the impact of the use of BDA on firm performance. Moreover, this study is one of the first papers to attempt to review the implementation of BDA in the banking industry. The combination of the TOE framework and dynamic capabilities is used to explain the relationship between TOE factors, the data dimension, BDA dynamic capabilities, risk management, and bank performance. Several factors from the TOE framework can be indicators of success when using BDA solutions: IT infrastructure readiness, BDA skills, data quality, and top-level management support. Therefore, the use of BDA is highly likely to increase the effectiveness of banks' risk management. In addition, many theoretical studies have shown methods to enhance BDA capability, mainly based on the resource-based view and dynamic capabilities theories. This study showed that BDA usage is inconsistent with four assumptions of VRIN in RBV theory, but is consistent with the three capabilities in dynamic capability: adaptive capability, absorptive capability, and innovative capability. Therefore, we suggest that banks should carefully consider these capabilities when planning to use BDA. This means that the practical use of BDA should be directed towards creating adaptive, absorptive, and innovative capability. According to our conceptual framework, the use of BDA to create these dynamic capabilities will affect bank performance. This study proposes a model for assessing business-influencing factors, especially in the banking sector, based on the perspective of the banking industry combined with dynamic capability and the TOE framework. Arguments and evaluations from the built framework will help future researchers to reduce research time when building research models.

4.2. Practical contributions

This study provides a more realistic view of BDA in the banking sector. Whether BDA solutions will become a trend or something practical for business – particularly in the banking and finance sectors, where competition between established banks and new entrants such as tech giants is intensifying – remains to be seen. This study is the first report on the practical use of BDA in the banking sector. The opinions of bank managers and experts confirmed that BDA plays a particularly important role in the operations of banks. BDA is used in functional areas such as risk management, fraud, crime detection, sales and marketing, and customer relationships. This means that there is a lot of room for banks or Big Data solution providers to advance BDA to improve other areas. The influencing factors presented in this study will help bank managers to comprehensively evaluate the projects of Big Data initiatives. The results of this paper also suggest that bank executives should pay more attention to the organizational aspects of BDA, such as developing analytics skills and improving current IT infrastructure/data quality. In particular, dedicated support from top-level management through commitment and a focus on Big Data initiatives will ensure the effective use of BDA.

4.3. Limitations and future directions

A limitation of this study is that its scope is limited in terms of the banking industry. Further research is needed to investigate how BDA use affects other sectors. Another limitation is that our article proposes a framework based on sound expert opinion and literature review. We suggest that more quantitative studies are required to estimate the relationship of significant factors, the use of BDA, and its impact on banking.

References:

1. Aebi, V., Sabato, G., & Schmid, M. (2012). Risk management, corporate governance, and bank performance in the financial crisis. *Journal of Banking and Finance*, *36*(12), 3213–3226. https://doi.org/10.1016/j.jbankfin.2011.10.020
2. Alharthi, A., Krotov, V., & Bowman, M. (2020). Addressing barriers to big data. *Business Horizons*, *60*(3), 285–292. https://doi.org/10.1016/j.bushor.2017.01.002
3. Ali, Q., Salman, A., Yaacob, H., Zaini, Z., & Abdullah, R. (2020). Does Big Data Analytics Enhance Sustainability and Financial Performance ? The Case of ASEAN Banks. *Journal of Asian Finance, Economics and Business*, *7*(7), 1–13. https://doi.org/10.13106/jafeb.2020.vol7.no7.001
4. Ali, Q., Yaacob, H., Parveen, S., & Zaini, Z. (2021). Big data and predictive analytics to optimise social and environmental performance of Islamic banks. *Environment Systems and Decisions*, *41*(4), 616–632. https://doi.org/10.1007/s10669-021-09823-1
5. Ali, S. N. (2020). Big Data, Islamic Finance, and Sustainable Development Goals. *JKAU: Islamic Econ*, *33*(1), 83–90. https://doi.org/10.4197/Islec.33-1.6
6. Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108
7. Barney, J. B. (2014). How marketing scholars might help address issues in resource-based theory. *Journal of the Academy of Marketing Science*, *42*(1), 24–26. https://doi.org/10.1007/s11747-013-0351-8
8. Batko, K., & Ślęzak, A. (2022). The use of Big Data Analytics in healthcare. *Journal of Big Data*, *9*(1), 3. https://doi.org/10.1186/s40537-021-00553-4
9. Belhadi, A., Zkik, K., Cherrafi, A., Yusof, S. M., & El Fezazi, S. (2019). Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies. *Computers and Industrial Engineering*, *137*(July), 106099. https://doi.org/10.1016/j.cie.2019.106099
10. Braganza, A., Brooks, L., Nepelski, D., Ali, M., & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, *70*, 328–337. https://doi.org/10.1016/j.jbusres.2016.08.006
11. Chen, D. Q., Preston, D. S., Swink, M., Chen, D. Q., Preston, D. S., Swink, M., … Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems*, *32*(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364
12. Dumbill, E. (2013). Making sense of big data. *Big Data*, *1*(1), 1–2.
13. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E
14. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897–904. https://doi.org/10.1016/j.jbusres.2015.07.001
15. Fosso, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International*

Journal of Production Economics, *165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

16. Gangwar, H. (2018). Understanding the Determinants of Big Data Adoption in India. *Information Resources Management Journal*, *31*(4), 1–22. https://doi.org/10.4018/IRMJ.2018100101
17. Ghani, N. A., Hamid, S., Targio Hashem, I. A., & Ahmed, E. (2019). Social media big data analytics: A survey. *Computers in Human Behavior*, *101*, 417–428. https://doi.org/10.1016/j.chb.2018.08.039
18. Ghasemaghaei, M. (2018). Improving Organizational Performance Through the Use of Big Data Improving Organizational Performance Through the Use of Big Data. *Journal of Computer Information Systems*, *60*(5), 395–408. https://doi.org/10.1080/08874417.2018.1496805
19. Ghasemaghaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Decision Support Systems*, *101*, 95–105. https://doi.org/10.1016/j.dss.2017.06.004
20. Giebe, C., Hammerström, L., & Zwerenz, D. (2019). Big Data and Analytics as a sustainable Customer Loyalty Instrument in Banking and Finance. *Financial Markets, Institutions and Risks*, *3*(4), 74–88. https://doi.org/10.21272/fmir.3(4).74-88.2019
21. Grossman, R. L., & Siegel, K. P. (2014). Organizational Models for Big Data and Analytics. *Journal of Organization Design*, *3*(1), 20. https://doi.org/10.7146/jod.9799
22. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004
23. Gupta, S., Qian, X., Bhushan, B., & Luo, Z. (2019). Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective. *Management Decision*, *57*(8), 1857–1882. https://doi.org/10.1108/MD-06-2018-0633
24. Härle, P., Havas, A., & Samandari, H. (2016). Risk - The future of bank risk management. *McKinseyandCo Corp.*, 1–7.
25. Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D. J., & Winter, S. G. (2007). *Dynamic capabilities and organizational process*. *Dynamic Capabilities: Understanding Strategic Change in Organizations*.
26. Hung, J. L., He, W., & Shen, J. (2020). Big data analytics for supply chain relationship in banking. *Industrial Marketing Management*, *86*(July 2018), 144–153. https://doi.org/10.1016/j.indmarman.2019.11.001
27. Jabareen, Y. (2009). Building a Conceptual Framework: Philosophy, Definitions, and Procedure. *International Journal of Qualitative Methods*, *8*(4), 49–62. https://doi.org/10.1177/160940690900800406
28. Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. *Journal of Parallel and Distributed Computing*, *74*(7), 2561–2573. https://doi.org/10.1016/j.jpdc.2014.01.003
29. Kő, A., Fehér, P., & Szabó, Z. (2019). Digital Transformation – A Hungarian Overview. *Economic and Business Review*, *21*(3), 371–392. https://doi.org/10.15458/ebr.91
30. Kohli, R., & Grover, V. (2008). Business Value of IT: An Essay on Expanding Research Di-

rections to Keep up with the Times. *Journal of the Association for Information Systems*, *9*(1), 23–39. https://doi.org/10.17705/1jais.00147

31. Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, *34*(3), 387–394. https://doi.org/10.1016/j.ijinfomgt.2014.02.002
32. Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *International Journal of Logistics Management*, *29*(2), 676–703.
33. Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *META Group Research Note*, *6*(70), 1.
34. Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly*, *31*(1), 59–87.
35. Magyar Nemzeti Bank. (2020). *Fintech and digitalisation report 2020*. Budapest.
36. Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, *54*(July). https://doi.org/10.1016/j.ijinfomgt.2020.102190
37. Maroufkhani, P., Wan Ismail, W. K., & Ghobakhloo, M. (2020). Big data analytics adoption model for small and medium enterprises. *Journal of Science and Technology Policy Management*, *11*(4), 483–513. https://doi.org/10.1108/JSTPM-02-2020-0018
38. Miah, S. J., Vu, H. Q., Gammack, J., & McGrath, M. (2017). A Big Data Analytics Method for Tourist Behaviour Analysis. *Information and Management*, *54*(6), 771–785. https://doi.org/10.1016/j.im.2016.11.011
39. Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, *29*(3), 260–287. https://doi.org/10.1080/0960085X.2020.1740618
40. Morabito, V. (2014). *Trends and challenges in digital business innovation*. New York: Springer International Publishing.
41. Müller, O., Fay, M., & vom Brocke, J. (2018). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. *Journal of Management Information Systems*, *35*(2), 488–509. https://doi.org/10.1080/07421222.2018.1451955
42. Nobanee, H., Dilshad, M. N., Al Dhanhani, M., Al Neyadi, M., Al Qubaisi, S., & Al Shamsi, S. (2021). Big Data Applications the Banking Sector: A Bibliometric Analysis Approach. *SAGE Open*, *11*(4), 215824402110672. https://doi.org/10.1177/21582440211067234
43. OECD. (2015). *OECD Digital Economy Outlook 2015*. https://doi.org/10.1787/9789264232440-en
44. Park, J. H., & Kim, Y. B. (2019). Factors Activating Big Data Adoption by Korean Firms. *Journal of Computer Information Systems*, *0*(0), 1–9. https://doi.org/10.1080/08874417.2019.1631133
45. Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers*, *20*(2),

209–222. https://doi.org/10.1007/s10796-016-9720-4

46. Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects. *International Journal of Production Research*, *56*(15), 5206–5221. https://doi.org/10.1080/00207543.2018.1427900
47. Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: a qualitative study in retail. *Production Planning and Control*, *28*(11–12), 985–998. https://doi.org/10.1080/09537287.2017.1336800
48. Ravitch, S. M., & Riggan, M. (2016). *Reason and rigor: How conceptual frameworks guide research* (Second Edi). Sage Publications.
49. Schultz, B. (2013). Big data in big companies. *Baylor Business Review*, *32*(1), 20–21.
50. Shakya, S., & Smys, S. (2021). Big Data Analytics for Improved Risk Management and Customer Segregation in Banking Applications. *Journal of ISMAC*, *3*(3), 235–249. https://doi.org/10.36548/jismac.2021.3.005
51. Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, *70*, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001
52. Srivastava, U., & Gopalkrishnan, S. (2015). Impact of big data analytics on banking sector: Learning for Indian Banks. *Procedia Computer Science*, *50*, 643–652. https://doi.org/10.1016/j.procs.2015.04.098
53. Sun, N., Morris, J. G., Xu, J., Zhu, X., & Xie, M. (2014). ICARE: A framework for big data-based banking customer analytics. *IBM Journal of Research and Development*, *58*(5–6), 1–9. https://doi.org/10.1147/JRD.2014.2337118
54. Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the Factors Affecting the Organizational Adoption of Big Data. *Journal of Computer Information Systems*, *58*(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891
55. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1093/0199248540.003.0013
56. Tornatzky, L. G., & Fleischer, M. (1990). *Processes of technological innovation*. Lexington books.
57. Troilo, M., Bouchet, A., Urban, T. L., & Sutton, W. A. (2016). Perception, reality, and the adoption of business analytics: Evidence from North American professional sport organizations. *Omega (United Kingdom)*, *59*, 72–83. https://doi.org/10.1016/j.omega.2015.05.011
58. Van Rijmenam, M. (2014). *Think bigger: Developing a successful big data strategy for your business*. New York: AMACOM.
59. Verma, S., & Chaurasia, S. (2019). Understanding the Determinants of Big Data Analytics Adoption. *Information Resources Management Journal*, *32*(3), 1–26. https://doi.org/10.4018/IRMJ.2019070101
60. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. fan, Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
61. Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews*, *9*(1), 31–51. https://doi.org/10.1111/j.1468-

2370.2007.00201.x

62. Wang, F. Y. (2012). A big-data perspective on AI: Newton, Merton, and analytics intelligence. *IEEE Intelligent Systems*, *27*(5), 2–4.
63. Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, *70*, 287–299. https://doi.org/10.1016/j.jbusres.2016.08.002
64. Wang, Y. M., Wang, Y. S., & Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, *77*(5), 803–815. https://doi.org/10.1016/j.techfore.2010.03.006
65. Welch, T. F., & Widita, A. (2019). Big data in public transportation: a review of sources and methods. *Transport Reviews*, *39*(6), 795–818. https://doi.org/10.1080/01441647.2019.1616849
66. Zhou, Z. H., Chawla, N. V, Jin, Y., & Williams, G. J. (2014). Big data opportunities and challenges: Discussions from data analytics perspectives [discussion forum]. *IEEE Computational Intelligence Magazine*, *9*(4), 62–74.
67. Zhu, L., Yu, F. R., Wang, Y., Ning, B., & Tang, T. (2018). Big Data Analytics in Action, 266–294. https://doi.org/10.4018/978-1-5225-7609-9.ch009