Hantos Elemér Doctoral School of Business, Management and Regional Sciences
University of Miskolc
Faculty of Economics

Phan Dai Thich

Big data analytics usage by banking sector in European Countries

PhD thesis

Academic supervisor:
Prof. Dr. Kovács Levente

Head of the Doctoral School:
Prof. Dr. Sikos T. Tamás

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1. Introduction

1.1 Justification of the topic

Among the emerging digital technologies, big data analytics is arising as the game changer in business (Fosso Wamba et al., 2017), as the fourth paradigm of science (Strawn, 2012), as a next frontier for innovation, competition, and productivity (Manyika et al., 2011). As one of the new technologies shaping the future of the banking sector, big data (BD) offers numerous benefits to banks since it enables banks to analyze customer behavior better and support better decision-making that can improve their operations. Big data technology can be incredibly advantageous for the banking sector since it enables banks to analyze customer behavior better and support better decision-making that can improve their operations. Banks can also utilize big data technology to detect fraud quickly and accurately and gain insights into customer preferences that can then be used to create more personalized products and services. Further, big data technology allows banks to build smarter and more efficient models to identify and target the right customers with relevant offers. Overall, big data technology is a powerful tool to help banks significantly improve their efficiency and profitability. (Raguseo, 2018) pointed out that the advantages of utilizing big data among studied enterprises are tremendous, and can be divided into four categories: strategic, transactional informational, and transformational benefits. Despite the numerous advantages associated with BDA projects, many enterprises have found that managing them has become the most pressing problems (Raguseo, 2018), thus big data is not widely used in enterprise (Frank et al., 2019).

Although the BDA market value is projected to reach above 650 billion dollars in 2029 (Statista, 2023) and 70% of enterprises in EU will use BDA (European Commission, 2022), the current low percentage of enterprises using BDA in general, and in banking especially, poses many challenges for countries in this region.

1.2 Introducing the research field.

The research on the use of BDA at the enterprise level is varied. However, in the banking and financial sector, it is scattered and limited to certain geographic markets such as the United States, China, the United Kingdom, and India (Nobanee et al., 2021). Research on BD in banking mainly focuses on customer analytics to increase customer retention and achieve competitiveness (Nobanee et al., 2021) and emphasizes the impact of BDA on banking operations. In a study on sustainability capabilities, Ali et al. (2020) combined the four factors, including green supply chain management, green human resource practices, commitment, and big data integration, to investigate the relationship between these factors and bank performance in terms of financial and environmental performance. The results from this study confirmed the role of green practices in supply chain management and human resource, combined with big data association, leading to an improved financial and environmental performance at commercial banks. Although not directly referring to BDA, Zelenka & Podaras (2021) used case studies from the banking sector to highlight the importance of data quality in business intelligence for creating tactical knowledge that effectively impacts decision-making. Risk management is an area of interest due to the rising cyber impacts on banking operations. Meanwhile, the banking sector is considered one of the primary data-driven industries in terms of applying new information technologies for management (Grover et al., 2018). A recent study, Milojević & Redzepagic (2021) briefly introduced how using artificial intelligence (AI), machine learning (ML), deep learning (DL), and BDA in risk management practices at banks. Furthermore, this research proposed a framework for using these cutting-edge techniques in building and developing risk management methods. The use of ML, DL, and AI are increasingly being promoted in risk management at banks. In the future BDA' contribution to the use of AI, ML, and especially DL is undisputed; it can create greater efficiency in risk management (Milojević & Redzepagic, 2021). Combining big data technology and Monte-Carlo method, Manuylenko et al. (2021) proposed a model for evaluating the potential strategic innovation risk in the banking sector. Previous researchers also highlighted the prospect of adopting big data technology in support of the era of bank of future. However, empirical studies on big data usage in the banking sector remain scarce.

1.3 Aims and main questions of the research

The existing studies on BDA in the banking sector are very limited, but most published studies are limited to its benefits and prospects. Despite the importance of big data technology, there remains a paucity of evidence on the understanding of the role of BDA capabilities in the performance of banks. To the best of my knowledge, no published studies in this sector show empirical evidence on how factors from technology organization environment framework (TOE), resource-based view (RBV), and dynamic capabilities theory (DC) could be combined to lead to banks' competitive advantage. This study would be the initial contribution to this aspect. This thesis seeks to fill the gap in the literature by proposing a model that combines RBV, TOE, and DC theory. It empirically investigates the effects of BDA usage on market performance and risk management performance.

Therefore, there are three primary aims of this study:

R1: to examine the relevant theories in context of BDA.

R2: to investigate empirically which factors influence the usage of BDA.

R3: to examine the relationship between BDA usage and banking performance.

In order to achieve these aims, the thesis attempts to answer the following research questions (RQ):

RQ1. What are the relevant theories in context of BDA usage at enterprise level?

RQ2. What are the determining factors of BDA usage in the EU-27 Member States' banking sector?

RQ2.1 What is the impact of top management support on BDA usage in the EU-27 Member States' banking sector?

RQ2.2 What is the impact of BDA skills on BDA usage in the EU-27 Member States' banking sector?

RQ2.3 What is the impact of BDA infrastructure on BDA usage in the EU-27 Member States' banking sector?

RQ2.4 What is the impact of big data quality on BDA usage in the EU-27 Member States' banking sector?

RQ3. Does BDA usage influence banking performance in the EU-27 Member States' banking sector?

RQ3.1 Does BDA usage influence market performance in the EU-27 Member States' banking sector?

RQ3.2 Does BDA usage influence risk management performance in the EU-27 Member States' banking sector?

The overall structure of this thesis takes the form of seven chapters, including:

Chapter 1 is the introduction of the thesis. In this chapter, the author explains the digital transformation trend in economies and the significance of utilizing digital technologies to enrich banking performance. The research aims and hypothesis are also presented in this chapter, followed by a brief introduction of the scope and methodology.

Chapter 2 presents more in-depth analysis about the digital transformation progress in the banking sector. After that, this thesis highlights some dominant frameworks for digital transformation in the banking industry. Moreover, two case studies of digital transformation in two Hungarian commercial banks are examined. Finally, the last two sections of chapter 2 present the understanding of BDA and the current trend of using this technology in the EU-27 Member States.

Chapter 3 is concerned with the literature review part. A comprehensive literature review was conducted. By laying out the relevant theories in using digital technology research, this chapter highlights the advantages and drawbacks of each of these single theories.

Chapter 4 develops the research model and presents research hypotheses. The research model proposes the relationship between 4 factors: top management support, BDA infrastructure, BDA skills, big data quality and BDA usage. This chapter also presents the relationship between BDA usage and bank performance, including risk management and market performance. Furthermore, the mediating relationship and direct relationship between these 4 factors and banking performance are established in this chapter.

Chapter 5 is the methodology part. This chapter presents the data material used for the quantitative analysis of this thesis. Moreover, the reason for selecting the Partial least square–structural equation modeling (PLS-SEM) method also is mentioned. The data collection method is presented in this chapter.

Chapter 6 presents the results and discussion. The section begins by examining the main results of the PLS-SEM method, including assessing the measurement and structural model. After a discussion of the results of the quantitative analysis, this chapter highlights the key findings and compares and contrasts the results of this thesis with previous studies.

Finally, **Chapter 7** emphasizes this study's theoretical contributions to the research field's current knowledge and the practical implications for business. The limitations and suggestions for future research are also mentioned.

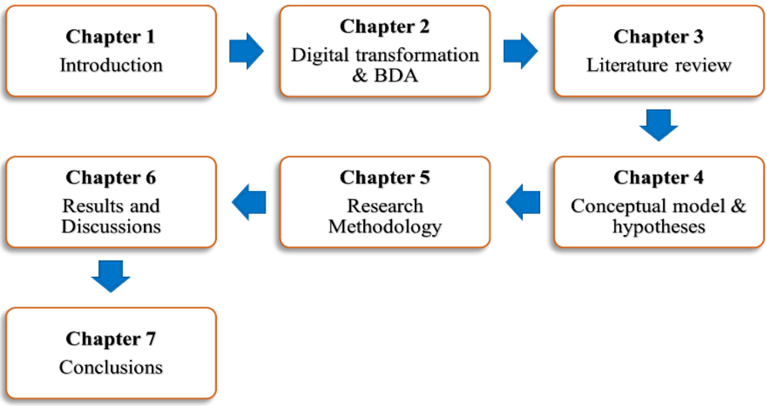

Figure 1: Research structure of the thesis
Source: Own edition

2. Theoretical basis and proposal research model

2.1 Technology Environment Organization Framework

The technology-organization-environment framework was introduced in 1990 by Tornatzky & Fleischer (1990). After that, the TOE framework has become a widely-used theory in adopting information technology to explain IT adoption at the firm level (Lai et al., 2018; Verma & Chaurasia, 2019). According to Tornatsky and Fleischer (1990), many factors that impact the adoption of innovation in firms can be grouped into three main contexts: technological, organizational, and environmental. *The technological context* indicates all the applicable technologies in usage at firms or in the marketplace. *The organizational context* indicates the typical features or inner resources of organizations. This context includes communicating style in firms, reporting relationships, working structures, and top management support toward innovative changes. Meanwhile, *the environmental context* indicates factors from the external environment such as competition in the industry, the level of use of new technology from customers, suppliers, third parties, and the relevant regulatory aspect. Many studies based on TOE assess the factors influential in the adoption of information technology and information systems in firms (Hsu et al., 2014), such as cloud serve adoption (Hsu & Lin, 2016); big data adoption (Maroufkhani, Wan Ismail, & Ghobakhloo, 2020; Park & Kim, 2019).

2.2 Resource-based view theory

The resource-based view (RBV) is the most popular and effective theory in investigating the impact of information technology on firm performance. The RBV was originally first addressed by Penrose (1959) who viewed firms as repositories of physical and human resources. Based on the RBV, Barney (2014) argued that the firm's performance depends on the attributes/ quality of its resources and capabilities. The RBV theory was based on two main assumptions about resources (Barney, 1991). Firstly, the strategic resources of firms in an industry are heterogeneous. Secondly, these strategic resources cannot be easy to mobilize among firms. The RBV posits that firms are composed of a distinct set of idiosyncratic resources and capabilities (Grant, 1996). Resources are central to the RBV (Curado & Bontis, 2006); however, there are different types of resources varying across industries and evolving over time, thus rendering the concept of resources dynamic. Many previous researchers have also employed RBV in studies Ghasemaghaei (2018); Gunasekaran et al. (2017); M. Gupta & George (2016).

2.3 Dynamic capabilities theory

The dynamic capabilities expanded from a RBV of the firm and attempted to explain how firms achieve competitive advantages in dynamic markets (Eisenhardt & Martin, 2000). According to Teece et al. (1997), dynamic capabilities emphasize two important aspects of competitive advantage that have been neglected in previous strategy studies. Term "dynamic" means changing the business environment; dynamic also refers to the capacity to renew competencies to fit with the volitale business environment (Teece et al., 1997). "Capabilities" emphasizes the key role of strategic management, including three important stages: adapting, integrating, and reconfiguring all resources, skills, and functional competencies in responding to changing environments. Dynamic capabilities are considered an emerging and potentially integrative approach to understanding the newer competitive advantage sources (Teece et al., 1997). RBV pays attention to resources, while dynamic capabilities emphasize organizational and strategic routines (Eisenhardt & Martin, 2000). In big data research, many authors applied dynamic capabilities theory as a foundation theory S. Gupta et al. (2019), Ghasemaghaei et al. (2017).

2.4 Proposal research model

BDA capabilities created from the usage of BD is considered as a organizational dynamic capability (innovative capabilities) through the combination of key resource factors to produce new services/ products or new way of working within enterprises (S. Gupta et al., 2019).

The combined factors between TOE and RBV affect the use of BDA in banks. In which BDA infrastructure is the element taken from the TOE framework. In RBV, BDA infrastructure is referred to as technical or intangible resources. This resource would have an impact on the BDA capability which was referred to as the usage of BDA. Meanwhile BDA skills are in the organizational dimension from TOE. According to RBV, human skills are considered as a type of human resource. Top management support is in the organization dimension in TOE. In RBV, the support from top management is another type of interrelation, managerial resource, which contributes to creating firm capabilities. The role of top managers in identifying and acquiring the winning resources becomes very important for businesses, even creating the economic performance of firms (Curado & Bontis, 2006). Throughout this study, the term BDA usage refers to innovative capabilities based on deploying BDA, such as creating new methods, products, and products in the bank. In digital transformation, enterprises attempt to achieve innovative things by combining and exploring BDA human resources, data, technology resources, and management expertise. As a result, these enterprises could achieve a sustainable competitive advantage. Thus, this process of using BDA should become a dynamic capability within enterprises (Braganza et al., 2017).

This thesis proposes a theoretical model based on the integration of the TOE framework, the Resource-based view, and the dynamic capability theory, consisting of two main components.

Four factors (independent variables) include top management support, BDA infrastructure, BDA skills, and big data quality. These four exogenous variables are hypothesized to impact BDA usage significantly.

Three dependent variables are BDA usage, risk management, and market performance. BDA usage is hypothesized to impact risk management performance and market performance significantly. One control variable is bank size (total assets).

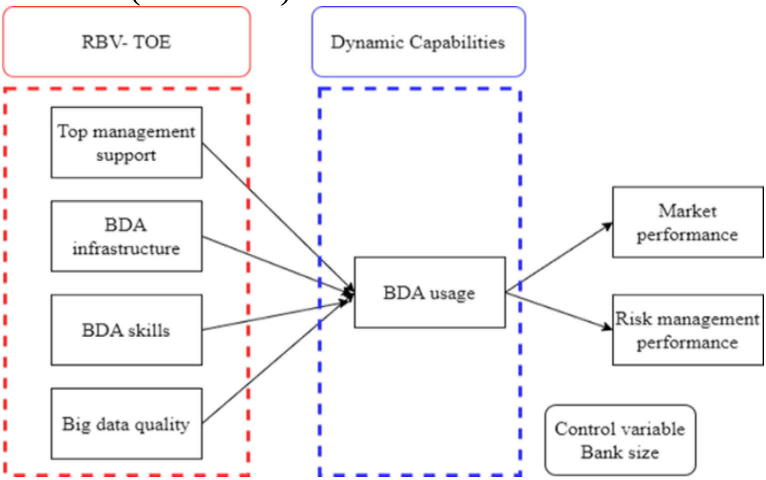

Figure 2: The proposal model of this thesis

Source: Own edition

3. Research methodology

3.1 Data collection

This research utilized primary data from a survey questionnaire to evaluate proposal research hypotheses. The survey consists of four sections. The first section is the research introduction, which includes the purpose and author information of the research. The second section is the demographic section, which includes four questions about respondents' age, types of banks, functional department, and total assets of their working banks. The main sections of the survey questionnaire (sections 3 and 4) used a 5-Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

A final survey questionnaire was generated using Google form and send to the qualified respondents via a professional network and emails between 1 October 2022 and 31 December 2022. The target respondents were those with experience in digital transformation and big data projects at their respective banks, most of whom were mid-level managers, such as department heads or team leaders. Totally 128 responses were collected, the response rate was at 12.1%. Only 114 bank-level responses in the EU-27 Member States were used for analysis due to missing values in performance assessment (see more at table 1).

Table 1: Respondent's demographic information

Characteristic	Criteria	Frequency (*n* = 114)	Percentage (%)
Age	20-29 years old	25	21.9%
	30-49 years old	78	68.42%
	50 years old or older	11	9.68%
Bank types	Commercial bank	104	91.23%
	Cooperative bank	5	4.39%
	Others (Saving banks, …)	5	4.39%
Department	General management	7	6.14%
	Information Technology	32	28%
	Data management, Business Intelligent	40	35%
	Risk management/Controlling/ AML/ Compliance/	16	14.04%
	Marketing/ Customer services	10	8.77%
	Others:	9	8.05%
Total Assets	More than EUR 100 billion	37	32.46%
	Between EUR 50 - 100 billion	29	25.44%
	Less than EUR 50 billion	48	42.10%

Source: Own edition

3.2 Assess measurement model

This research employed partial least square–structural equation modeling (PLS-SEM) to examine the relationship between four factors (namely BDA infrastructure, BDA skills, top management support, and big data quality) and the dynamic capabilities of using BDA. This study utilizes the SEMinR package on the R environment to implement PLS-SEM.

Table 2: The measurement model result

Variables	Indicator	Loading factor	Factor Loading Square	Cronbach's alpha	CR	AVE	rhoA
BDA infrastructure	INF1	0.861	0.742	0.92	0.94	0.759	0.927
	INF2	0.811	0.658				
	INF3	0.873	0.762				
	INF4	0.911	0.83				
	INF5	0.896	0.803				
BDA skills	SKILL1	0.837	0.701	0.909	0.937	0.787	0.91
	SKILL2	0.889	0.79				
	SKILL3	0.927	0.859				
	SKILL4	0.894	0.8				
Big data quality	DQ1	0.813	0.662	0.749	0.856	0.663	0.768
	DQ3	0.81	0.656				
	DQ4	0.822	0.676				
Top management support	TOP1	0.902	0.814	0.919	0.942	0.803	0.929
	TOP2	0.882	0.779				
	TOP3	0.912	0.832				
	TOP4	0.889	0.79				
USAGE	USAGE1	0.868	0.753	0.904	0.929	0.723	0.906
	USAGE2	0.851	0.725				
	USAGE3	0.84	0.706				
	USAGE4	0.854	0.729				
	USAGE5	0.837	0.701				

Risk management	RP1	0.895	0.801	0.901	0.931	0.771	0.915
	RP2	0.872	0.761				
	RP3	0.84	0.706				
	RP4	0.903	0.815				
Market performance	MP1	0.758	0.574	0.894	0.927	0.763	0.898
	MP2	0.91	0.828				
	MP3	0.915	0.836				
	MP4	0.901	0.812				
Size	Size	1	1	1	1	1	1

Note: CR: Composite reliability; AVE: Average variance extracted

Source: Own edition

In order to evaluate PLS-SEM results, the measurement model was evaluated by assessing the relevant different criteria (Hair, Risher, Sarstedt, & Ringle, 2019). These criteria suggested are examining the indicator reliability, internal consistency reliability, composite reliability and construct reliability (Hair et al., 2019).

Next step of assessing the measurement model is evaluating the internal consistency reliability by checking the composite reliability (CR). In order to evaluate the convergent validity of each construct, the average variance extracted (AVE) was used to examine. The last step to assess the measurement model is examining the discriminant validity. Table 2 indicates that all constructs and indicators, except DQ2, were satisfied with the criteria of evaluating the measurement model. Hair et al. (2022) suggested that the HTMT values should be used to check the discriminant validity. Table 3 shows that HTMT values were lower than the threshold value of 0.9 which confirms discriminant validity is not present.

Table 3: The heterotrait-monotrait ratio result

	INF	**SKILL**	**TOP**	**DQ**	**USAGE**	**Size**	**MP**	**RP**
INF								
SKILL	0.868							
TOP	0.736	0.798						
DQ	0.697	0.664	0.639					
USAGE	0.663	0.694	0.543	0.552				
Size	0.086	0.180	0.124	0.091	0.232			
MP	0.532	0.591	0.500	0.426	0.599	0.200		
RP	0.545	0.470	0.379	0.428	0.512	0.155	0.694	

Source: Own edition

3.3 Assessing the structural model

The results, as shown in table 4, demonstrated the results of bootstrapping process with path coefficient, t-value and confidence intervals. The findings showed that the impact of top management support was insignificant with a path coefficient of -0.001. The impact of BDA infrastructure on the BDA usage was insignificant with a path coefficient of 0.251. The result from table 4 did support the relationship between BDA skills and the BDA with path coefficient of 0.369. Meanwhile, the impact of data quality on the BDA usage was insignificant with path coefficient of 0.116. Therefore, the study confirmed hypothesis H3, while H1, H2, H4 were rejected. This implies that, among the four factors under investigation, only BDA skills exert a statistically significant influence in the BDA usage.

The second set of analyses investigated the impact of BDA usage on banking performance. As shown in table 4, BDA usage had a significant positive impact on both market performance and risk performance, thus H5 & H6 were accepted.

Table 4: Results of path analysis

Hypo	Main Model	Path coefficients	t-value	2.5% CI	97.5% CI	Result
H1	TOP → USAGE	-0.001	-0.009	-0.218	0.220	Rejected
H2	INF → USAGE	0.251	1.738	-0.048	0.518	Rejected
H3	**SKILL → USAGE**	**0.369****	**2.928**	**0.123**	**0.620**	**Accepted**
H4	DQ → USAGE	0.116	1.282	-0.056	0.302	Rejected
H5	**USAGE → RP**	**0.460*****	**5.800**	**0.297**	**0.606**	**Accepted**
H6	**USAGE → MP**	**0.527*****	**7.265**	**0.379**	**0.665**	**Accepted**
Control variable		**Path coefficients**	**t-value**	**2.5% CI**	**97.5% CI**	
Bank size → MP		0.073	0.965	-0.075	0.218	
Bank size → RP		0.049	0.541	-0.124	0.226	

Source: Own edition

Table 5 revealed that there was no significant indirect effect between BDA infrastructure and market performance & risk management performance. However, interestingly, this study discovered a significant direct relationship between BDA infrastructure and risk management performance, with path coefficient of 0.330.

Table 5: The results of the mediating effect

Hypo	Mediating effect (Indirect and direct relationship)	Path coefficients	t-value	2.5% CI	97.5% CI	Result
H7	TOP→USAGE→MP	-0.000	-0.009	-0.115	0.122	No effect
H1a	TOP → MP	0.127	0.999	-0.126	0.374	
H8	TOP→USAGE→RP	-0.000	-0.009	-0.104	0.104	No effect
H1b	TOP →RP	-0.042	-0.343	-0.288	0.193	
H9	INF→USAGE→MP	0.132	1.738	-0.027	0.276	No effect
H2a	INF → MP	0.047	0.330	-0.227	0.337	
H10	INF→USAGE→RP	0.115	1.666	-0.022	0.168	Only direct
H2b	INF → RP	0.330	2.490	0.065	0.591	
H11	SKILL→USAGE→MP	0.195	2.531	0.060	0.360	Full mediating
H3a	SKILL → MP	0.186	1.155	-0.114	0.514	
H12	SKILL→USAGE→RP	0.169	2.568	0.053	0.313	Full mediating
H3b	SKILL → RP	-0.030	-0.201	-0.308	0.279	
H13	DQ→USAGE→MP	0.061	1.235	-0.029	0.168	No effect
H4a	DQ → MP	0.035	0.306	-0.193	0.248	
H14	DQ→USAGE→RP	0.053	1.170	-0.024	0.157	No effect
H4b	DQ → RP	0.125	1.137	-0.103	0.327	

Source: Own edition

Of particular importance, the study identified a significant mediating effect of BDA usage on the relationship between BDA skills and market performance and on the relationship between BDA skills and risk management performance. Meanwhile, the direct relationship between BDA skills and martket performance and risk management performance variables were found to be insignificant with coefficients of 0.186 and -0.03 respectively. According to the suggestion from Zhao et al.

(2010), this situation was classified as full mediation. This means that the relationship between BDA skills and both market performance and risk management performance were completely mediated by BDA usage.

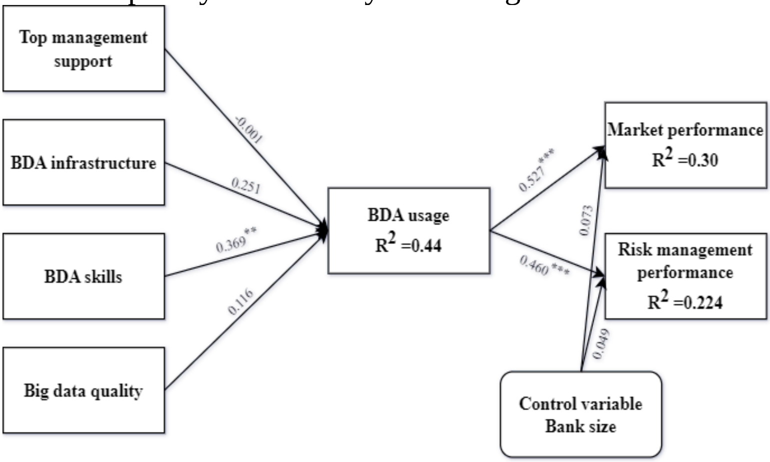

Figure 3: Result of path analysis
Source: Own edition

4. New and novel statement of the research

4.1 The role of top management support

The striking result of this study highlighted that top management support had no significant impact on BDA usage. This result contrasts with previous studies which have found that top management support had a significantly positive effect on the adoption (Lai et al., 2018; Verma & Chaurasia, 2019) and usage (Chen, Preston, & Swink, 2015) of BDA. Meanwhile, this finding supports evidence from previous observation by Braganza et al. (2017, p. 334), who found that "big data initiatives begin with issues business leaders consider important strategically". This finding also is supported by previous study of Gurău & Ranchhod (2020). although top management support found to be insignificant on the impact to BDA usage, this finding did not mean to underestimate the role of top management support, however, it could be explained by the fact that in banking sector, the top management supports often play an important role in kick-starting big data initiatives. They can initiate the benefits of big data by discussing with colleagues or big data experts within the organization. Furthermore, as decisions to adopt BDA in the early stages often involve third parties and require adherence to establishing standard security policies (Verma & Chaurasia, 2019), and adoption of BDA is a big decision so that the support of top management is of great importance at this stage (Baig, Shuib, & Yadegaridehkordi, 2021). After this stage, leveraging BDA as a dynamic capability to develop new services/products, this stage will depend on human skills and capabilities.

4.2 The relationship between BDA infrastructure and BDA usage

The results of this study indicate that BDA infrastructure has an insignificantly positive impact on BDA usage. This result is supported by Lai et al. (2018)'s finding but it is inconsistent with findings from Verma & Chaurasia (2019) which emphasizes the essential preparation of infrastructure for BDA adoption. This result can be attributed to the fact that banking is the most IT-driven sector, and banks in EU-27 regions have achieved a certain degree of infrastructure in using BDA. Moreover, many banks already have used 4V characteristic of big data. For instance, in order to exploit insight from real time data, banks invested in establishing their own big data centers to foster the availability of adopting BDA solutions. Therefore, the findings from this study suggested that BDA infrastructure is no longer a barrier to banks using big data technologies. This results may be different with findings from other sectors (Fosso Wamba, Akter, & de Bourmont, 2019).

4.3 The relationship between BDA skills and BDA usage

The result suggested that BDA skills were the most important factor influencing BDA usage. This finding is consistent with the results of Akter et al. (2019) and Fosso Wamba et al. (2017), who highlighted that personnel expertise was the most significant component of BDA capability. Additionally, this finding supports the assertions of Debortoli et al. (2014) that big data projects are highly dependent on human capital. Similarity, Gurău & Ranchhod (2020) highlighted the importance of humans in the implementation of new technologies, which are seen as a means for organizations to achieve their business objectives. The results from this study highlighted the role of human skills in the BDA capabilities of banks. Data sources could be exploited efficiently and effectively in order to create innovative capabilities through highly qualified employees and well-educated staff.

4.4 The relationship between big data quality and BDA usage

The statistical data showed that BDA characteristic quality did not have significant influence on the BDA usage. It is interesting to note that solely using big data with 4V's characteristics did not create BDA dynamic capabilities for banks, then had no impact on banking performance. This finding is contrary to previous study which have suggested that big data is firm capability (Ghasemaghaei, 2018). It has been suggested that data asset and big data experts in IT-intensive sectors would allow enterprises achieve better performance (Müller, Fay, & vom Brocke, 2018). This interesting result seem to be consistent with previous study (Lai et al., 2018). The observed result may be due to the fact that banks' big data initiatives are still in their infancy, some small banks may not need all the features offered by complicated BDA applications and should only select the ones beneficial for their banks and market situation.

4.5 The relationship between BDA usage and market performance

The result from the statistical analysis showed that using BDA has a significantly positive influence on market performance in the banking sector. This result is consistent with findings from previous studies (Maroufkhani et al., 2020; Raguseo, 2018; Yadegaridehkordi et al., 2020). Raguseo (2018) concluded that one of the main benefits from using big data is allowing companies response and improve their products and service faster than competitors. Moreover, using big data technologies helps companies react faster in the dynamic changing environment (Raguseo, 2018). This study's findings corroborate the conclusions of Manuylenko et al. (2021). This study found that the advantages of BDA are no longer merely potential; the quantitative results demonstrate that the utilization of BDA directly contributes to the bank's operations by creating dynamic and innovative capabilities, allowing the bank to deliver products and services faster, better, and with a higher success rate, thus enabling them to capture a larger market share.

4.6 The relationship between BDA usage and risk management performance

The quantitative result highlighted that using BDA in creating innovative products/ services has significantly positive influence on risk management performance in the banking sector. According to Milojević & Redzepagic (2021), AI and ML would be likely to contribute more effective on the performance of risk management, meanwhile, BDA provide as the foundation which moderate this relationship stronger. This study provided empirical evidence on the direct impact of using BDA on the practices of risk management at banks in Europe. Through helping banks identify, measure, and controlling the related risk in daily operation, banks would likely to reduce the possibility of risk exposures.

4.7 The mediating role of BDA usage

The result of the statistical analysis showed that the usage of BDA mediated the relationship between BDA skills and market performance and risk management performance. This finding provides evidence that supports the efficacy of dynamic capabilities in the context of big data. In this study, strategic resources such as human skills do not have a direct impact on market performance and risk management performance. In context of big data technology, this study discovered that having high-quality BDA staff could contribute to improving bank performance through creating innovative services/products or developing new methods for identifying fraud in banking operations.

The result from the mediating analysis highlighted that the relationship between BDA infrastructure, top management support and big data quality and banking performance was not significantly mediated through the usage of BDA. This finding suggests that the innovative services and products in the banking sector, which depend on the use of BDA, are limited by regulatory factors. As a result, banks require a significant amount of time to achieve improved outcomes, even when they invest in BDA infrastructure.

This study discovered that BDA infrastructure directly enhances banks' ability to improve risk management practices. This conclusion suggests that banks should invest more in BDA infrastructure in order to gain better results, such as identifying fraud quickly with real-time data and calculating risks faster.

5. Conclusion and further research directions

5.1 Theoretical contribution

The research results demonstrated that the combination of the TOE, RBV, and DC theory provides a meaningful explanation for the competitive advantage of firms in terms of market and risk management performance. The significant factors in using BDA align with the TOE and the Resource-Based View (RBV) theory. The successful implementation of BDA requires combining strategic resources, such as BDA infrastructure, skills, top management support, and big data quality. This study empirically demonstrates the importance of human resources (BDA skills) in relation to innovative dynamic capabilities for successfully using BDA technology. Particularly, BDA skills are highlighted as the sole significant factor for effectively implementing digital technologies such as BDA in the banking sector.

The findings of this research demonstrate that resource-based views (especially human resources) can serve as a basis for developing dynamic capabilities, thus enabling banks to gain a competitive advantage.

The results from this empirical study provided solid evidence that using BDA should be considered a dynamic organizational capability at the enterprise level. Furthermore, in the banking context, this study found that using BDA allows banks to generate innovative capabilities by supporting new services/ products. These innovative capabilities, then, help banks enhance banks competitive advantages. In this study, the competitive advantage of banks was investigated concerning risk management performance and market performance.

5.2 Pratical implications

The insights gained from this study contribute to our understanding of using BDA in the banking sector in one of the most developed regions in the world.

First, the quality of human resources to meet the requirements of the BDA is of utmost importance in the operation and exploitation of the advantages provided by the BDA. The capabilities of the BDA are evaluated in terms of training and recruitment. Using BDA in the banking industry necessitates technical skills and a basic background in banking and finance.

Second, the results from the study suggest many policy implications for governments and administrative managers. For policymakers, more focus should be placed on programs to enhance digital skills for the public and big data skills for younger generations who will work in related jobs in the future. BDA. More specifically, for universities, which provide the main workforce for the banking sectors, it is necessary to supplement students with quantitative and programming skills and business knowledge.

5.3 Further research directions

In the future, new technologies are often be interlinked, and BDA will go along with applying AL, ML, cloud computing, and chatbots in operations. Future studies should expand the research model further to assess the overall impact of these digital technologies in the future of banking to different aspects of comparative advantages.

Future research should expand the assessment of new factors, such as data cultures and fintech cooperations, that can affect the practices of managing BDA to increase the model's explanatory power and strengthen the theories.

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