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Big data analytics usage in the banking industry in Tanzania: does perceived risk play a moderating role on the technological factors

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Justus Mwemezi
Department of Banking and Financial Services, Institute of Finance Management, Dar es Salaam, United Republic of Tanzania, and
Herman Mandari
Department of Computer Science, Institute of Finance Management, Dar es Salaam, United Republic of Tanzania

Abstract

Purpose – The main purpose of this paper is to examine the adoption of big data analytics (BDA) in the Tanzania banking industry by investigating the influence of technological, environmental and organizational (TOE) factors while exploring the moderating role of perceived risk (PR).

Design/methodology/approach – The study employed a qualitative research design, and the research instrument was developed using per-defined measurement items adopted from prior studies; the items were slightly adjusted to fit the current context. The questionnaires were distributed to top and middle managers in selected banks in Tanzania using the snowball sampling technique. Out of 360 received responses, 302 were considered complete and valid for data analysis. The study employed partial least squares structural equation modeling (PLS-SEM) to examine the developed conceptual framework.

Findings – Top management support and financial resources emerged as influential organizational factors, as did competition intensity for the environmental factors. Notably, bank size and perceived trends showed no significant impacts on BDA adoption. The study's novelty lies in revealing PR as a moderating factor, weakening the link between technological readiness, perceived usefulness and the intent to adopt BDA.

Originality/value – This study extends literature by extending the TOE model, through examining the moderating roles of PR on technological factors. Furthermore, the study provides useful managerial support for the adoption of BDA in banking in emerging economies.

Keywords Tanzania, Banking industry, Big data analytics, Adoption, Perceived risk

Paper type Research paper

1. Introduction

Big data analytics (BDA) is emerging as a popular technology in the fourth industrial revolution. Researchers and businesses are very interested in this subject. Big data is considered a revolutionary change in several industries and is becoming a more popular research topic (Tran, 2022). Big data may provide countless insights and valuable information for businesses that use it to accelerate the transformation process (Mikalef & Krogstie, 2020). Small and medium-sized businesses (SMEs) employ BDA to generate

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business value in terms of strategic, transactional, transformational and informational value, which benefits the firm's market performance and financial performance (Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020).

The development of information technology (IT) and the internet has produced enormous amounts of data across numerous businesses. BDA is derived from big data, which is the process of analyzing large volumes of data through which industries and various organizations (like banks, e-commerce and insurance) can learn about various individuals' spending patterns and correlations. This aids these industries in discovering new opportunities, which in turn results in wiser business decisions, increased profits and happier customers. Conventional tools cannot provide such information. Big Data is therefore created to offer a method of handling this data so that industries can accelerate their growth rate. According to Mikalef and Krogstie (2020), despite the significance of BDA in the banking sector and the high cost of infrastructure investment for BDA, there is still a dearth of data on the key elements determining the successful usage of BDA in banks. Additionally, even though social studies have a lot to say about the uses and efficacy of BDA, there has been little in-depth research into how to create an implementation framework that produces results from the usage of BDA in successful and efficient banks. One industry that is seen as an early adoption of IT for data-driven decision-making is banking (Gupta, Gupta, Agrawal, Agrawal, & Kansal, 2019). A significant competitive advantage for banks is the ability to store vast quantities of consumer data regarding interaction channels. The financial technology concerns are complex, but they exhibit some consistency because most studies on big data issues focus on situations in industrialized nations. FinTech considerations in these nations differ substantially from one another. Tanzanian banks are catching up to their foreign competitors, but much scope remains. Research on technology adoption in the banking sector reveals differences between developing and developed countries due to differences in innovative advancements in banking technologies. The findings of Kevin, Benard and Ronald (2013) on the adoption of information and communication technology (ICT) in the Tanzanian Banking Sector suggest that while some factors are consistent across countries, there are also factors in each country. The researcher concluded that in Tanzania, for example, banks should invest more in ICT infrastructure, educate the public about the use of online banking products and lower fees on ICT devices.

For this reason, it is interesting to understand better the BDA usage in the banking industry in the developing countries like in Tanzania. Unfortunately, there has not been much research done on BDA in the banking industry. Furthermore, as far as we know, no effort has been made to empirically analyze the moderating effects of perceived risk (PR) on technological factors and BDA adoption.

Tanzania's IT scene constantly evolves, and its IT industry faces several difficulties. Like in many other countries, PRs influence the adoption of big data technologies and practices in Tanzania (Richard & Mandari, 2018). We think that organizations can quickly adopt BDA by developing comprehensive strategies that reduce PRs. As organizations rely on erroneous or low-quality data for their analytics, it can result in incorrect insights and poor decision-making, ensuring data quality and accuracy is essential, and the risk of doing so can be a big worry (Alyoussef & Al-Rahmi, 2022). Accordingly, Chaurasia and Verma (2020) found that organizations must employ strong security measures and adhere to data protection laws to reduce the dangers of PRs. For instance, firms' worries about the future return on investment, the resources needed for data infrastructure, qualified staff, and the difficulty of developing and managing systems can impact BDA adoption decisions.

This study examines whether BDA improves bank performance and offers a conceptual model to assess the influence of factors affecting the adoption of BDA in the banking industry. The model treats the PRs as a moderating variable affecting the banks' technology context. Based on Tornatzky and Fleischer (1990), the technological, environmental and organizational (TOE) model does not consider the PR in adoption of technologies. However, Kumar, Singh, Kumar, Khan, and Corvello (2023) explained that PR is the main element impeding the adoption of new technologies. Furthermore, Im, Kim, and Han (2008) suggested PR as a moderator in the technology acceptance model (TAM) model. Similarly, Ho, Ocasio-Velázquez, and Booth (2017) proposed that PR in the theory of planned behavior (TPB) model moderates the impact of the drivers of behavior intention. Likewise, PR was conceptualized as a moderator in the UTAUT2 model by Susanto, Hoque, Hashim, Shah, and Alam (2020). Therefore, it is clear that PR can be conceptualized as moderating factor that impact technological factors on BDA adoption. Analyzing the relationship between technological factors and PR (Kumar *et al.*, 2023) concerning BDA adoption could produce exciting and unique findings. The analysis's findings could assist decision-makers in pinpointing the elements that need to be prioritized more than others to increase banking operations' efficiency and effectiveness in using BDA compared to what Tanzania's commercial banks are now doing. Consequently, this study addresses the following questions.

RQ1. Do the TOE factors influence the adoption of BDA in Tanzanian commercial Banks?

RQ2. Does the risk factor impact technological factors in adopting BDA in Tanzania Commercial Bank?

2. Literature review

2.1 Big data

According to Dubey, Gunasekaran, Childe, Blome, and Papadopoulos (2019) and Liu, Soroka, Han, Jian, and Tang (2020), BDA refers to a term used to describe applying advanced analytics techniques to examine the vast data set of businesses. According to Ghasemaghaei and Calic (2020), "big data" refers to vast amounts of real-time accessible, structured and unstructured data. Several academics and practitioners have described big data using the "Vs" concept. Volume, variety and velocity were listed as the three distinctive characteristics of big data (Russom, 2011). The volume discusses the enormous amount of data produced and gathered in the modern business environment, including through mobile devices and web apps (Ghasemaghaei & Calic, 2020). Variety is defined as a range of data models, including structured, semi-structured and unstructured data that are difficult to evaluate using conventional analytic tools and come from various sources (Mohapatra & Mohanty, 2020). The speed of data generation and real-time data analysis to gather insights and practical information is called velocity (Shukla, Muhuri, & Abraham, 2020).

2.2 The need for big data analytics in the Tanzania banking sector

Big data assists in paving the way for revolutionary changes in several industries, including inventions and marketing statistics. BDA is essential in the banking sector since the quantity of client data is multiplying and will impact the level of service provided (Singh, Singh, Gahlawat, & Prabha, 2022). It enables banks to simplify their operations and save time and money. Big data also aids in account analysis, enabling banks to determine borrowers' repayability. With the aid of big data, banks can review the data to monitor consumer behavior in real time, assisting the sector in determining how many requirements are required at any given moment (Merhi & Bregu, 2020). However, adopting BDA solutions is considered expensive and difficult to implement (Gupta *et al.*, 2019; Mikalef & Krogstie, 2020; Tran, 2022). When employing BDA, Alharthi, Krotov and Bowman (2017) recognized how crucial it was to remove obstacles in its path. These obstacles are due to technological obstacles like infrastructure preparedness and data complexity, human obstacles like skill gaps and organizational obstacles like organizational culture and confidentiality. Given the significant data that banking institutions have stored for many years, the big data revolution occurring in and around the 21st century has resonated with them. Since then, this data has helped analyze consumer behavior, prevent massive disasters and robberies and unlock hidden financial movements. Banks benefit the most from big data since they can now rapidly and easily extract useful information from their data and transform it into advantageous outcomes for both them and their clients. Internationally, banks are starting to use data to their advantage in various ways, including sentiment analysis, product cross-selling, regulatory compliance management, reputational risk management, financial crime management and many other things (Hasan, Hoque, & Le, 2023).

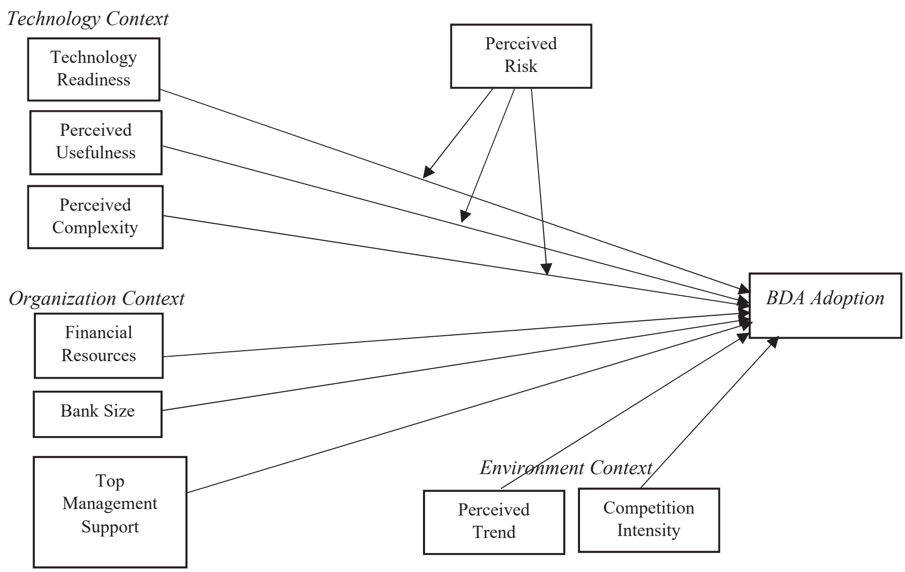
Four observable trends exist in the use of BDA by banks in the Big Data era. First, banks can better understand customer behavior by utilizing vast data on demographics, financial situations and transaction behaviors based on over-the-counter transaction channels, ATMs, mobile apps, internet channels and social media (Ali, Salman, Yaacob, Zaini, & Abdullah, 2020; Merhi & Bregu, 2020). Giebe, Hammerström, and Zwerenz (2019) argued that employing BDA can boost client loyalty by providing customer advisory services. Second, to detect fraud more effectively and manage risk, banks utilize big data regarding volume, velocity and diversity (Shakya & Smys, 2021). Third, compared to traditional data analysis, BDA allows banks to process large amounts of data faster, improving efficiency. Fourth, BDA allows banks to handle enormous amounts of data more quickly than they could with traditional data analysis, which boosts their productivity (Gupta *et al.*, 2019; Tran, 2022).

3. Conceptual framework and hypotheses development

3.1 Conceptual framework development

BDA has significantly impacted the banking sector, revolutionizing how financial organizations run, make decisions and treat their clients. The application of BDA in banking may be examined through the TOE framework. Numerous studies have supported the ability of TOE in explaining various technologies' adoption in an organizational setting (El-Haddadeh, Osmani, Hindi, & Fadlalla, 2021; Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2020; Oliveira, Martins, Sarker, Thomas, & Popovi_c, 2019). The fundamental advantage of TOE is that it considers internal and external aspects in a single model, which sets it apart from other theories that explain technology adoption, such as institutional theory, knowledge-based view and technology structuration theory (Saetang, Tangwannawit, & Jensuttiwetchakul, 2020). Similarly, Awa, Ukoha, and Emecheta (2016) explained that due to the combinations of factors considered for adoption, TOE provides more holist insight on technological adoption that other theories which considered attitudinal factors only. Therefore, this study adopts the TOE framework to examine the adoption of BDA in the banking sector in Tanzania.

Prior research has made the dubious assumption that TOE factors are independent (Iranmanesh, Lim, Foroughi, Hong, & Ghobakhloo, 2023). Furthermore, considering Susanto *et al.* (2020) proposal in their study of e-money behavior that PR is associated with technological acceptance and behavioral theories, we believe that PRs are linked with the effects of technological factors when adopting BDA in the banking business. As a result, considering that final decisions to adopt BDA are based on the magnitude of PRs, this study includes PR as a potential moderating variable. The likelihood of implementing BDA is low when the PR is significant, regardless of how advanced technological, organizational and environmental elements are. Consistently, this study challenges the idea that each TOE is independent and the model includes PR as a moderator between the technological environment and BDA adoption. The proposed conceptual framework is shown in Figure 1.



Source(s): Created by authors

Figure 1. Proposed conceptual framework

3.2 Technology readiness

Technology readiness refers to the ability of an organization to integrate and efficiently use cutting-edge technologies, such as BDA tools and systems. It includes several elements: technological infrastructure, IT capabilities and workforce digital skills (Chen, Liu, & Lin, 2013). Maroufkhani *et al.* (2020) define an organization's preparedness to adopt a technology as being determined by its availability to financial, technological and trained human resources. Consistently, technological readiness in the present work refers to a bank's readiness and capacity to accept and use cutting-edge technology to improve operations, enhance client experiences and maintain competitiveness in the digital era. Related research has revealed a link between BDA and technological readiness (Aziz, Long, & Wan Hussain, 2023; Maroufkhani, Iranmanesh, & Ghobakhloo, 2023; Saetang *et al.*, 2020). Similarly, future trends in BDA technology readiness are highlighted by recent studies (Huang, Yao, Krisp, & Jiang, 2021), including the incorporation of artificial intelligence (AI), the growing use of cloud-based solutions and the introduction of blockchain for data security. Therefore, we propose that:

H1. Technology readiness has a positive and significant influence on the BDA adoption.

3.3 Perceived usefulness

One of the core concepts of Davis' Technology Acceptance Model (TAM) is perceived usefulness (Davis, 1989). It describes the extent to which a person thinks utilizing a specific technology would improve their ability to accomplish their job. The adoption of numerous technologies, particularly BDA tools, has frequently utilized this idea (Iranmanesh *et al.*, 2023). The influence of perceived usefulness on adopting BDA has been the subject of several studies (Alamsyah, Setyawati, & Rohaeni, 2022; Alyoussef & Al-Rahmi, 2022; Eresia-Eke, Mojalefa, & Nyanga, 2023). These findings demonstrate that consumers are more inclined to embrace and utilize new technology when they believe technologies would benefit their duties, performances and decision-making processes. In the context of financial institutions and the implementation of BDA, Li, Chen, Wang, Pei, and Yue (2020) discovered that perceptions of usefulness directly impacted intentions to utilize BDA technologies, highlighting their importance in this industry. Thus, the following hypothesis is proposed:

H2. Perceived usefulness has a positive and significant influence on the adoption of BDA.

3.4 Perceived complexity

Perceived complexity, as described, is “the degree to which an innovation is considered to be difficult to understand and use.” The detrimental effect of complexity on adopting new technology has been demonstrated in earlier studies (Kapoor & Dwivedi, 2020). If technology integration into business operations is simple, adoption is more likely. Maroufkhani *et al.* (2023) claimed that complexity is the most significant barrier to technology adoption. Prior empirical studies have indicated that complexity has a negative and significant impact on the adoption of a variety of technologies, including big data, blockchain, cloud computing and intelligent agent technology (Al-Dmour, Saad, Basheer Amin, Al-Dmour, & Al-Dmour, 2023; Gangwar, Hema, & Ramaswamy, 2015; Maroufkhani *et al.*, 2023; Mukherjee & Chittipaka, 2022). Consequently, the following hypothesis is put forth.

H3. Complexity has a negative and significant influence on the adoption of BDA.

3.5 Financial resources

A bank’s financial capability is a major factor in its potential to implement BDA (Al-Dmour *et al.*, 2023). They argued that banks with ample resources are better equipped to spend money on infrastructure, talent and innovative data analytics technologies. According to studies by Ilin, Ivetić and Simić (2017), the level of BDA implementation in banking is positively correlated with financial resources. Aziz *et al.* (2023) have also produced conceptually related work, arguing that managing costs and assuring the alignment of BDA initiatives with strategic goals are significant issues for banks, particularly those with low financial costs. In order to optimize their processes, financial institutions with abundant resources can invest in cutting-edge automation systems (Al-Dmour *et al.*, 2023; Al-Khatib, 2022; Lian, Yen, & Wang, 2014). Therefore, this study postulates that:

H4. Financial resources have a positive and significant influence on the adoption of BDA.

3.6 Bank size

More recent work from Al-Khatib (2022) postulated that, larger banks typically have more resources and data sources, making investing in and using BDA technologies simpler. Because larger businesses typically have the financial resources to be better equipped and implement innovations. In earlier empirical studies, firm size has been recognized as an essential determinant of technology adoption (Shi, Chen, Zhao, & Xu, 2022; Zhu, Kraemer, & Xu, 2006). Rogers (2004) even claimed that larger companies should encourage the adoption of innovations because they typically have resource advantages. For instance, small firms have more challenges when implementing e-business since they frequently lack resources (El Rassi, 2020). On the other hand, given their resource advantages, larger enterprises are more likely to implement e-business because it requires financial, technological and managerial resources (Zhu *et al.*, 2006). However, there were conflicting findings. Recent studies indicated no significant correlation between corporate size and digital acceptance or technology adoption (Cho, Cheon, Jun, & Lee, 2022; Nguyen, Le, & Vu, 2022). As a result of this contradiction, there is a need to test the influence of bank size on adopting the BDA. Therefore, this study hypothesizes that:

H5. Bank size has a positive and significant influence on the adoption of BDA.

3.7 Top management support

Top management support is crucial for effective technology adoption since it measures the extent to which managers comprehend and embrace the technological capabilities of a new technology system (Maroufkhani *et al.*, 2020; Mukherjee & Chittipaka, 2022). However, top management support can significantly hinder the adoption of business analytics (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Top management support creates an organizational strategy for implementing the newest technology, provides the funding for its implementation and encourages and supports employees in adopting it (Abed, 2020; Alharbi, Atkins, & Stanier, 2016; Gangwar *et al.*, 2015; Iranmanesh *et al.*, 2023). Therefore, this study hypothesizes that:

H6. Top management support has a positive and significant influence on the adoption of BDA.

3.8 Perceived trend

Reviewing the perceived trend and use of BDA in the banking sector indicates a quickly changing environment necessitated by the demands of customer-centricity, data-driven decision-making, risk management and operational effectiveness. According to Nguyen *et al.* (2022), the perceived trend represents the degree to which companies believe they are following the most cutting-edge technological trends. Li (2020) argues that the trending of the internet of things (IoT), AI and BDA are among the technologies organizations increasingly focus on for digital transformation. Previous empirical research showed the positive role of perceived trends in picking and implementing innovations, indicating their favorable effects (Kim & Ko, 2012; Nguyen *et al.*, 2022). Based on the literature, this study postulates that:

H7. Perceived trend has a positive and significant influence on the adoption of BDA.

3.9 Competition intensity

According to Sun, Hall, and Cegielski (2020), competition intensity is the degree of pressure a firm feels from its competitors within the same industry. Pressure from partners and rivals influences the desire to embrace IT (Alsaad, Mohamad, & Ismail, 2019; Pizam *et al.*, 2022). Companies are encouraged to implement innovations like BDA by competition intensity (Iranmanesh *et al.*, 2023). The adoption of new technologies and the establishment of organizations are influenced by industry competitiveness. Innovation is necessary for businesses to better their company strategy and stay competitive. The intensity of competition would possibly force banks to reap the advantages of BDA. According to Maroufkhani *et al.* (2023), managers and owners may be persuaded to invest in BDA to preserve the company's competitive position by competitors' increasing usage of BDA. The level of industry competition may encourage businesses to use BDA's benefits (Sun *et al.*, 2020). As a result, this study postulates that:

H8. Competition Intensity has a positive and significant influence on the adoption of BDA.

3.10 The moderating role of perceived risk

PR refers to distrust towards potential negative consequences of using a service or product (Alyoussef & Al-Rahmi, 2022; Liu & Tao, 2022). PR is considered before using the system when people make decisions about the size and particularity of a risk. Zhang, Wang, and Liang (2021) recommend emphasizing the importance of multifaceted risk perception when considering a framework for implementing new technologies. Big data deployment is problematic, considering its PRs are essential due to several vital dangers identified by the McKinsey Global Institute (Di Vaio, Hassan, & Alavoine, 2022). Therefore, this research uses this PR factor to measure banks' attitudes toward readiness, usefulness and complexity to adopt BDA in their business. According to Iranmanesh *et al.* (2023), PR negatively modifies SMEs' intentions to embrace BDA and propensities to outsource BDA. Ho *et al.* (2017) noted that a user's trust intention toward cloud adoption – which influences their choice to use cloud technology – is strongly influenced by their subjective standards and PR. Specifically, our study suggests that bank officers' adoption of BDA may be influenced by PR, acting as a moderating factor. The relationship between the dependent variable (BDA adoption) and the independent factors (technological readiness, perceived usefulness and perceived complexity) will be moderated by PR. More specifically, when PR is present, the link between and among these factors will be weakened (Jain & Raman, 2023). Put differently, PR has the potential to reduce the impact of perceived usefulness, perceived complexity and technological readiness. To investigate this further, we put forth the subsequent three hypotheses:

H9a. PR negatively moderates the relationship between Technology readiness and BDA adoption.

H9b. PR negatively moderates the relationship between perceived usefulness and BDA adoption.

H9c. PR negatively moderates the relationship between perceived complexity and BDA adoption.

4. Research methodology

4.1 Research instrument development

The modified TOE model was tested using a survey questionnaire with reliable and valid constructs adapted from earlier research. Sixteen (16) items for measuring technology readiness (optimism, innovation, discomfort and insecurity) were adapted from Chen *et al.* (2013). Four items for PR were adapted from Matos and Krielow (2019), four items for perceived usefulness, six items for perceived complexity, four items for top management and three items for BDA adoption adapted were from Abdekhoda, Dehnad, and Zarei (2019), three items for financial resources and three items for competition intensity were adapted from Ilin *et al.* (2017), three items for bank size and three items for perceived trend were adapted from Nguyen *et al.* (2022). With anchors ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), a five-point Likert scale was used to evaluate each item (see Appendix 1). A pretest was performed to ascertain the content validity and reliability of the research constructs prior to the main study (Ikart, 2019). The questionnaire was pretested by three academicians and two managers from the banking sector (DeMaio & Landreth, 2004; Ikart, 2019). Minor changes were made based on the suggestions and views of the academics and industry professionals. The pretest was administered to ten respondents who were chosen from a sample of the study's population to complete the survey without any coaching, and we then gathered their comments to make sure they understood all the terminology and ideas in the questionnaire (Babonea & Voicu, 2011). As suggested by Dikko (2016), the pilot study was conducted to establish the validity and reliability of each construct's measuring indicators, only 8 (two from each of the four variables: optimism, innovation, discomfort and insecurity) were loaded. Consequently, the other eight items were not included in the main survey. The questionnaire was modified to create the final questionnaire for the main survey. Additionally, a skip question was added to eliminate respondents who were not in managerial roles at the bank because this study only included respondents with sufficient understanding of bank operations and managerial positions to represent the bank (Maroufkhani *et al.*, 2023).

4.2 Sampling and data collection

Out of 45 Tanzanian commercial banks, a sample of 4 institutions was chosen to conduct an empirical analysis of the research framework. The rationale behind this choice is that the four banks, that is, the National Microfinance Bank (NMB), Cooperative and Rural Development Bank, National Bank of Commerce (NBC) and EXIM Bank, together own approximately 70% of the industry's total assets (TanzaniaInvest, 2023) and dominate the Tanzanian banking sector. These banks have been doing business in Tanzania for more than 20 years, with the highest levels of digitalization (TanzaniaInvest, 2023). Since the data were collected from the branches of the sampled banks, the websites of these banks were used to determine the population of their branches. Three hundred and fifty-five (355) top and middle managers of these banks were used as a sample group who represented their banks (Alam & Islam, 2021). The collection of data involved distributing the questionnaires to the top and middle-level managers because participants were required to have sufficient expertise to respond to questions about the influence of BDA on the banks (Saetang *et al.*, 2020). Eresia-Eke *et al.* (2023) also assert that management-level staff are more aware of concepts like BDA.

To gather data, the snowball sampling technique was utilized to distribute the questionnaires (Al-Khatib, 2022). The survey did, however, include a cover letter outlining the study's objectives and what BDA entailed. The two months of July and August 2023 were used to collect the data. The researchers made two-week interval follow-up calls and 308 (85.5%) of the 360 respondents who received the questionnaire submitted their responses. However, after screening the data set, 302 questionnaires were considered to be complete and valid for subsequent data analysis. The profiles of the participants who represented their banks are shown in Table 1. Overall, 43.7% of survey participants were bank officers and 56.3% of respondents were managers and directors of banks. Approximately 78.5% of the participants in the survey have more than six years of banking experience. In comparison, 21.5% of the respondents have experience ranging from 1 to 5 years. 84.8% of the banks that responded to a survey had more than 100 branches and 15.2% had between 1 to 100 branches.

Since the data were gathered from a single person using a self-reported questionnaire, common method bias (CMB) may have been present, inflating the relationships within the model (Podsakoff, MacKenzie, & Podsakoff, 2012). Research suggests that CMB is deemed ineffective if the generated variance inflation factor (VIF) falls below the suggested threshold of 3.3 (Diamantopoulos, Riefler, & Roth, 2008; Kock, 2015). The findings in Table 2 demonstrate that all VIFs are less than 3.3. Therefore, it is concluded that CMB is not a concern and there is no collinearity.

4.3 Data analysis techniques

Partial least squares structural equation modeling (PLS-SEM) was used to evaluate the study's conceptual framework. PLS-SEM is a more suitable statistical method to analyze the theoretical model of this study than an alternative strategy, such as covariance-based

Demographic	Category	Frequency	Percentage
Respondent's position	Manager	121	40.1
	Director/Chief	49	16.2
	Officer	132	43.7
Respondent's experience	0 years – 5 years	65	21.5
	6 years and above	237	78.5
Number of branches	1–100 branches	46	15.2
	101–200 branches	83	27.5
	201 and above branches	173	57.3

Source(s): Created by authors

Table 1. Participants' demographic data

Construct	Item	VIF	Factor loading	CR	AVE
BDA adoption (BDAA)	BDAA1	1.642	0.829	0.874	0.699
	BDAA2	1.529	0.800		
	BDAA3	1.888	0.877		
Bank size (BS)	BS1	1.771	0.735	0.883	0.718
	BS2	1.913	0.880		
	BS3	1.901	0.916		
Financial resources (FR)	FR1	1.881	0.964	0.906	0.829
	FR2	1.610	0.853		
	FR3	1.501	0.829		
Perceived intensity (PI)	PI1	1.826	0.835	0.910	0.717
	PI2	2.314	0.856		
	PI3	2.087	0.826		
	PI4	2.284	0.868		
Perceived risk (PR)	PR1	1.492	0.736	0.848	0.583
	PR2	1.315	0.756		
	PR3	1.589	0.757		
	PR4	1.723	0.804		
Perceived trend (PT)	PT1	1.996	0.826	0.884	0.718
	PT2	1.635	0.876		
	PT3	1.803	0.838		
Perceived useful (PU)	PU1	1.633	0.745	0.873	0.632
	PU2	1.478	0.802		
	PU3	1.872	0.838		
	PU4	1.746	0.792		
Perceived complexity (PC)	PC1	1.537	0.713	0.892	0.579
	PC2	1.811	0.781		
	PC3	1.708	0.723		
	PC4	1.808	0.777		
	PC5	2.011	0.811		
Technological readiness (TR)	TR1	1.798	0.807	0.934	0.638
	TR2	2.379	0.841		
	TR3	2.691	0.785		
	TR4	2.722	0.869		
	TR5	2.753	0.817		
	TR6	2.007	0.735		
	TR7	2.364	0.754		
	TR8	2.427	0.774		
Top management support (TMS)	TMS1	2.118	0.744	0.872	0.630
	TMS2	1.678	0.844		
	TMS3	1.882	0.785		
	TMS4	1.661	0.799		

Source(s): Created by authors

Table 2.
Reliability and validity of measurement model

modeling, because this study is prediction-oriented (Hair, Sarstedt, & Ringle, 2019; Iranmanesh *et al.*, 2023). Smart-PLS software version 3 was used to analyze the data. Before evaluating the structural model by running the bootstrapping analysis, the study evaluated the measurement model to ensure its validity and reliability.

5. Results of the study

5.1 The assessment of the measurement model

It was necessary to assess the measurement model's internal reliability, discriminant validity and convergent validity. Factor loadings, composite reliability (CR) and average variance extracted (AVE) were evaluated to see whether the constructs were convergent. Factor loadings, AVE and CR values need to be higher than 0.7, 0.5 and 0.7, respectively, to attain convergent validity, discriminant validity and internal reliability (Hair, Joe, Matthews, Matthews, & Sarstedt, 2017). Findings from this study show that all factor loadings exceeded the recommended threshold of 0.7 (see Table 2) except for two items of technology readiness (TR6 and TR7), which were dropped. The outcomes verified that all AVE and CR values are significantly between 0.5 and 0.7, respectively, indicating the fulfillment of convergent validity.

To determine the discriminant validity, the Heterotrait–Monotrait (HTMT) criteria were examined (Henseler, Ringle, & Sarstedt, 2015). Table 3 shows that HTMT values are below 0.85, which is the recommended threshold (Kline, 2016). These findings indicate that our data met discriminant validity.

5.2 The assessment of the structural model

When the research's measurement model was confirmed, the structural model was evaluated using the following metrics: t-value, p-value, confidence intervals, coefficient of determination (R-square), effect size (f-square) and predictive relevance (Q-square) (Hair, Joseph, Hult, Ringle, & Sarstedt, 2021). Whether independent variables had an R-square effect over the dependent variable was determined. The R^2 value is 0.485, higher than the weaker or lower value of 0.25 (Hair *et al.*, 2016). It indicates a 48.5% effect of the independent variables over the dependent variable. The impact of the latent valuables (f-square) in the structural model was examined consistently. According to the effect size value conclusion, all attitudes had a small effect (0.02) on the model, with values ranging from 0.019 to 0.05 (Cohen, 1988).

It was found that six hypotheses (H1, H2, H3, H4, H6 and H8) were supported at 95% confidence intervals by carrying out a bias-corrected and accelerated (BCA) bootstrapping technique with 5,000 resamples (see Table 4). More specifically, it was discovered that the adoption of BDA in Tanzania's banking industry was positively influenced by TR ($\beta = 0.149$, $t = 1.398$, $p = 0.081$), PU ($\beta = 0.150$, $t = 2.714$, $p = 0.003$), TMS ($\beta = 0.155$, $t = 2.522$, $p = 0.006$) and PI ($\beta = 0.025$, $t = 0.439$, $p = 0.330$). However, in Tanzania's banking industry, it was found that PC ($\beta = -0.473$, $t = 7.592$, $p = 0.000$) and FR ($\beta = -0.011$, $t = 0.181$, $p = 0.428$) negatively influenced the adoption of BDA. Table 4 shows that two hypotheses (H5 and H6) were unsupported. Accordingly, it can be concluded that neither PT nor BS significantly affect the adoption of BDA ($\beta = 0.062$, $t = 0.710$, $p = 0.239$; $\beta = 0.039$, $t = 0.716$, $p = 0.237$). Consistently, the blindfolding was done to ascertain the degree of predictive relevance of the study's endogenous constructs. According to Hair *et al.* (2021), the model had a predictive relevance on the adoption of BDA because the Q^2 score (0.320) was determined to be greater than 0.

	BDAA	CP	PI	PMS	FR	PR	BS	TR	PT	PU
BDAA										
CP	0.748									
PI	0.284	0.411								
TMS	0.568	0.600	0.356							
FR	0.051	0.055	0.050	0.051						
PR	0.398	0.452	0.408	0.712	0.077					
BS	0.159	0.198	0.099	0.107	0.063	0.097				
TR	0.111	0.068	0.055	0.059	0.726	0.084	0.065			
PT	0.095	0.065	0.048	0.054	0.699	0.077	0.091	1.053		
PU	0.526	0.524	0.349	0.569	0.071	0.491	0.198	0.037	0.037	

Source(s): Created by authors

Table 3. Discriminant validity (HTMT)

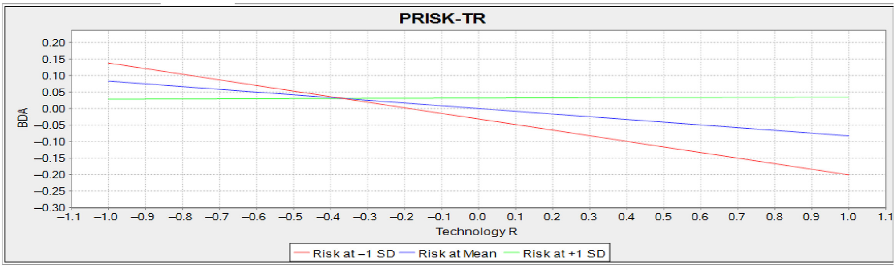
Hypotheses	Relationships	Path coefficients	t-values	p-values	Remarks
Main model					
H1	TR → BDA +	0.149	1.398	0.081*	Supported
H2	PU → BDA +	0.150	2.714	0.003*	Supported
H3	PC → BDA−	−0.473	7.592	0.000*	Supported
H4	FR → BDA−	0.011	0.181	0.428**	Supported
H5	BS → BDA+	0.029	0.555	0.289	Not supported
H6	TMS → BDA+	0.155	2.522	0.006*	Supported
H7	PT → BDA+	0.062	0.710	0.239	Not supported
H8	PI → BDA+	0.025	0.439	0.330*	Supported
Moderating effect of perceived risk to technological factors					
H9a	PRISK-TR → BDA	0.086	2.159	0.022*	Supported
H9b	PRISK- PU → BDA	0.098	2.065	0.2011*	Supported
H9c	PRISK-PC → BDA	−0.180	3.188	0.241*	Not supported

Note(s): *p < 0.05; **p < 0.01; ***p < 0.001
Source(s): Created by authors

Table 4.
Hypotheses testing

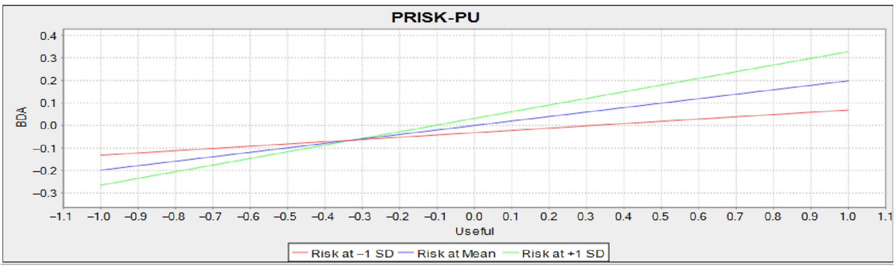
The moderating influence of PR was tested using a two-stage technique, as suggested by (Hair *et al.*, 2019). According to the results, the relationship between TR and BDA ($\beta = 0.088$, $t = 2.159$, $p = 0.015$), PU and BDA ($\beta = 0.105$, $t = 2.065$, $p = 0.019$) was shown to be negatively moderated by PR. However, PC on BDA ($\beta = -0.182$, $t = 3.188$, $p = 0.241$) was insignificant. As a result, the hypotheses for H9a and H9b were confirmed, while H9c was not.

The interaction graphs in Figures 2–4 clearly show how PR modifies BDA uptake. Figure 2 shows that while the intention to adopt BDA is positively influenced by technology



Source(s): Created by authors

Figure 2.
The moderating effect of perceived risk on technology readiness



Source(s): Created by authors

Figure 3.
The moderating effect of perceived risk on perceived usefulness

readiness, the relationship between the two is weaker when the PR is high and stronger when it is low. This implies that PR may lessen the chance of BDA adoption when banks are ready to implement it. Similarly, Figure 3 shows that while perceived usefulness positively impacts BDA uptake, there is a weaker link when PR is high and vice versa; hence, the hypotheses H9a and H9b are supported. Figure 4 shows that PR does not moderate the link between perceived complexity and BDA adoption. A higher PR is associated with a weaker relationship.

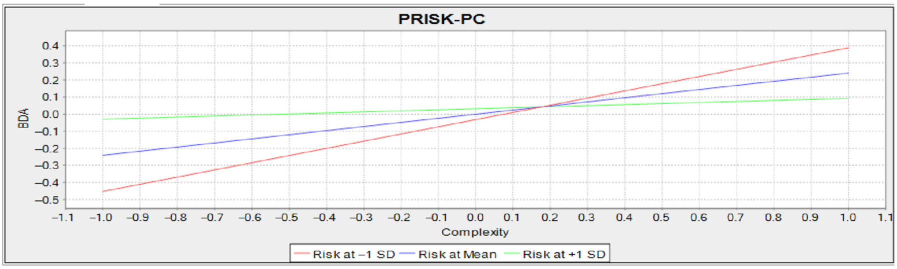
6. Discussion of results, theoretical and practical implications

6.1 Discussion of results

The analysis of the data yields many exciting findings. This study illustrates the adoption results of BDA in the banking sector. This study employed the TOE conceptual framework to achieve its objectives that statistically confirm the gap in the related literature (Tornatzky and Fleischer, 1990). One of the study's main objectives is to investigate how organizational, technological and environmental factors affect Tanzanian commercial banks' adoption of BDA. In the case of technological factors, the findings demonstrate that all technological factors (technology readiness, perceived usefulness and perceived complexity) influence the adoption of BDA. The outcomes were consistent with other prior empirical research that applied this approach to the banking industry, such as Al-Dmour *et al.* (2023).

Regarding organizational factors (financial resources, bank size and top management support), only financial resources and top management appear to positively and significantly impact adopting BDA in Tanzanian commercial banks; the bank size has no significant effect. Additionally, among the environmental factors, the competition intensity directly influences the adoption of BDA. However, the perceived trend has no significant influence on adopting BDA. The second objective was to examine the moderation analysis of PR factors and how they affect technological factors in Tanzania Commercial Bank's adoption of BDA. The findings show that PRs weaken the relationship between technological factors and BDA adoption in Tanzanian commercial banks. An investigation of the impact of technological readiness on BDA adoption by banks substantiated the relationship between technological readiness and BDA adoption. As with most research on technology adoption (Aziz *et al.*, 2023; Chen *et al.*, 2013; Maroufkhani *et al.*, 2023), the hypothesis results show that TR significantly influences banks' adoption of BDA. Banks with higher technology readiness levels for BDA are more likely to use BDA services.

H2 investigated how banks adopted BDAs and found confirmation of the influence of perceived usefulness (PU). PU is one of the main indicators of a person's intention to use technology (Davis, 1989). Like most research, the hypothesis results show that PU significantly affects banks' adoption of BDA. According to Davis (1989), this aligns with the TOE. The findings are also consistent with the studies examining the context of technology adoption (Abed, 2020; Al-Dmour *et al.*, 2023; Gloria & Achyar, 2018; Nguyen *et al.*, 2022;



Source(s): Created by authors

Figure 4.
The moderating effect of perceived risk on perceived complexity

Yuan *et al.*, 2016). The adoption of BDAs and complexity had a strong relationship (H3 supported). The solution's ease of use encourages banks to use and apply big data. Most earlier research agrees with the study's findings (Al-Dmour *et al.*, 2023; Gangwar *et al.*, 2015; Kapoor & Dwivedi, 2020; Yang, Sun, Zhang, & Wang, 2015). According to Davis (1993), one of the key elements influencing users' acceptance of new IT is its simplicity of use. The link between these two factors indicates that the complexity of BDA in banks significantly impacts banks' perceptions that adopting BDA rises with decreasing complexity.

Surprisingly, bank size and BDA adoption do not significantly correlate (H5), which is consistent with earlier research by Cho *et al.* (2022) and Nguyen *et al.* (2022). One possible explanation for the negligible impact is banks' experience with the broad use of several digital channels at a reasonable cost. As a result, even small firms with little funding are probably involved in adopting BDAs through interchangeable strategies (Maroufkhani, Wagner, Wan Ismail, Baroto, & Nourani, 2019). Nonetheless, another explanation would be that only large banks were included in the study's sample, which could have obscured the impact of size. Future research can investigate this further by merging banks of varying sizes. The impact of top management support (TMS) on banks' adoption of BDA was investigated in H6 and revealed that the results are consistent with most research in the context of technology adoption that looked at the impact of TMS on BDA (Abed, 2020; Al-Dmour *et al.*, 2023; Gangwar *et al.*, 2015; Iranmanesh *et al.*, 2023; Sumbal *et al.*, 2019). These studies found a significant positive relationship between big data adoption and top management support. This indicates that the implementation of innovation will be considerably facilitated by top managers' crucial role in allocating resources and maintaining a positive banking environment (Yadegaridehkordi *et al.*, 2020). Furthermore, Yadegaridehkordi *et al.* (2020) contend that the active participation and collaboration of managers as corporate decision-makers is crucial in implementing BDA. The acceptance and application of BDA Tanzanian banks are directly impacted by the degree to which a bank's manager or owner recognizes its benefits and attempts to participate in its initiatives.

According to the analysis for H4, another organizational factor determining the degree of BDA application practice is financial resources. The present investigation's results align with the earlier research (Al-Khatib, 2022; Aziz *et al.*, 2023; Ilin *et al.*, 2017). One of the main barriers to the adoption and use of big data is thought to be insufficient financial resources (Al-Dmour *et al.*, 2023; Lian *et al.*, 2014). In light of this, commercial banks should invest more money in adopting big data to benefit from this technology. Surprisingly, no evidence supports the relationship between BDA adoption and perceived trend (H7). This indicates that banks do not view perceived trends as motivating factors for implementing BDA. This contradicts other research that revealed banks were motivated to adopt technology by perceived trends (Kim & Ko, 2012; Li, 2020; Nguyen *et al.*, 2022). One probable explanation could be that Tanzanian banks have already migrated to digital platforms for their operational services; therefore, the perceived trend may not be the driving force behind adopting BDA. While the inclination to adopt technology in businesses rises with trendiness, in the case of banks, it might be more feasible to prioritize establishing other necessary structures before responding to the trend.

As previously noted by Alsaad *et al.* (2019) and Pizam *et al.* (2022), who discovered a substantial relationship between pressures from partners and competitors and intention to embrace IT, the results of this study validated the existing relationship between competition intensity and the adoption of BDA. With the entry of major international banks into Tanzania's local banking markets, adopting BDA is essential in this competitive sector. In an increasingly competitive market, banks are more likely to see BDA adoption as an essential tool for competitiveness and survival to maintain a competitive edge and successfully compete against adjacent competitors with BDA.

Lastly, the current study extended the earlier research that looked at the TOE model in the adoption of BDA by highlighting the crucial moderating role of PR for the relationship between independent variables of technological factors and the adoption of BDA (Al-Dmour *et al.*, 2023; Hashim, Saiful Bahry, & Shahibi, 2021; Tran, 2022). When PR is considered the moderator, the results showed a negative and substantial relationship between technological factors and intention to adopt BDA. Our findings are related to the study by Susanto *et al.* (2020), which found that PR negatively moderates and e-money along the UTUAT2. In brief, this study encapsulates a wide dimension of PR factors and uncovers the moderating role of PR on BDA adoption. More precisely, when PR is present, the link between technological factors and BDA adoption is weakened.

6.2 Theoretical and practical implications

Examining the use of BDA in the banking sector across Tanzanian banks is the main contribution of the current study to the BDA literature. The present study further adds to the literature by investigating the moderating effect of PR in the relationship between technological factors and BDA adoption. There has been little in-depth research on how to create an implementation framework that results in the successful and efficient use of BDA in banks, despite social studies having a lot to say about the uses and efficacy of BDA in various industries (Mikalef & Krogstie, 2020). Thus, with a foundation in TOE, the current study sought to determine the essential factors for BDA adoption in the banking sector and the moderating effect of PR on the adoption process. In contrast to earlier research, we take PR into account and offer empirical evidence for its significance in BDA uptake. The results of the moderating effects confirm the negative moderating effects on technological aspects of BDA adoption, adding new knowledge to the literature. Our results somewhat align with those of Susanto *et al.* (2020) study, which likewise discovered that PR negatively moderates technology adoption along the unified theory of acceptance and use of technology (UTAUT) model with E-Money behavior. From a practical standpoint, these results show that banks view BDA as involving some risk, especially when making adoption-related decisions. Tanzanian banks seem hesitant to adopt BDAs because they associate risk with technological factors (technology readiness, perceived usefulness and perceived complexity).

All technological factors had a substantial predictive impact on the adoption of BDAs. These results are consistent with the TOE framework's theory (Tornatzky and Fleischer, 1990). The results demonstrated that perceived usefulness, complexity and technological readiness are essential to persuading managers and banks to employ BDA. If managers and policymakers wish to take the lead in adopting BDA, they need to prioritize technology factors practically. Additionally, managers must comprehend that to facilitate the adoption of BDA, and they must hire specialist IT workers with skill sets spanning both the traditional IT environment and establish strategic projects to support business growth to enable BDA. Because the findings consistently demonstrated that perceived complexity has a negative impact on BDA adoption, bank experts and decision-makers should select big data systems that are simple to set up and manage. They should also oversee training programs and workshops to ensure staff members can easily handle related new technologies.

The results also showed that organizational factors, such as top management support, positively affect banks' adoption of BDA. Consequently, commercial banks are strongly advised to host regular seminars, workshops, and training sessions to emphasize the benefits of big data adoption and provide staff members with an understanding of big data systems, methodologies, strategies and procedures. Adoption and execution of BDA are directly impacted by the degree to which a manager or owner of an organization recognizes its benefits and tries to participate in its initiatives (Iranmanesh *et al.*, 2023). The analysis shows that banks' level of BDA application practice is influenced by their financial resources. One of the main barriers to adopting and using big data is insufficient financial resources (Lian *et al.*, 2014). Considering this, commercial banks should invest more money in adopting big data to benefit from this technology. Additionally, given their limited resources as operating banks in developing nations, banks should employ and purchase the most affordable big data technologies and models. However, conflicting findings were discovered regarding the organizational factor of bank size, which did not affect Tanzanian banks' adoption of BDA. This illustrates that, even though varying firm sizes influence their acceptability of technology, most banks have digitally transformed their operations, making the adoption of BDA inevitable. Consequently, banks of any size could implement BDA into their operations due to its advantages.

The impact of competition intensity on the intention to adopt BDAs was supportive from an environmental perspective. As a technical innovation, BDA creates a lot of economic chances. Non-adopters in diverse industries will be scared to lag adopters and look different. It might also encourage those who are not adopters to lead their industry in BDA adoption. Unexpectedly, we discovered a negligible correlation between BDA uptake and perceived trend. This suggests that practitioners should explicitly identify the long-term objective and plan for BDA adoption rather than waiting for management to observe market trends before implementing BDA. Managers should start addressing these problems as soon as the digital transformation begins. When it comes to investing in personnel and new technologies, managers should be proactive.

7. Limitations and future research direction

Although the study's goals were achieved, it had limitations, much like any other research work. This study provided the essential theoretical basis by providing a comprehensive analysis of the variables that could affect banks' adoption of BDAs via the lens of the TOE model. First, the findings may not be generalized to all other banks as the sample size of this study included only large banks; therefore, a further study that includes all banks of different sizes should be conducted. In addition, the sampling was convenient and snowball, which may affect generalization. Secondly, the study has used cross-sectional data, which may change over a short period. Based on these findings, if any bank takes longer to adopt BDA, it may have different outputs. Therefore, a longitudinal study may be further considered. Thirdly, this research could be extended in further studies by including more constructs, or a mix of other models – such as TAM and UTAUT – may be required to explain the adoption of BDA as the coefficient of determination *R*-square was 48.5%, indicating that still other factors could drive BDA adoption by commercial banks.

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Further reading

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. -H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347.

Appendix 1

Construct	Item Code	Measurement items	Reference
Technology readiness	TR1	BDA makes my bank to be more efficient	Chen *et al.* (2013)
	TR2	BDA gives my bank more freedom of flexibility in services provision	
	TR3	My bank offers BDA products and services without any help	
	TR4	Others come to my Bank for advice on BDA	
	TR5	BDA products and services rarely come with manuals that are expressed in simple terms	
	TR6	BDA technical support lines are not helpful because they don't explain things in terms that I understand	
	TR7	I worry about using BDA technologies in my bank	
	TR 8	It is not safe to do any financial business based on BDA techniques	
Perceived risk	PR1	My bank will not feel safe in using BDA to establish e-services strategies	Matos and Krielow (2019)
	PR2	The fear of data safety always discourages my bank from adopting BDA	
	PR3	Overall, my bank does not have confidence and security in applying for BDA	
	PR4	The risk of cyber threats that can compromise data discourages my bank from using BDA	
Perceived usefulness	PU1	The adoption of BDA will result in more efficiency in my bank	Abdekhoda, Gholami, and Zarea (2018)
	PU2	Adopting BDA will lead to the rapid provision of bank services to customers	
	PU3	Adopting BDA results leads to more success of the bank's objectives	
	PU4	Adopting BDA in my bank will enable employees to accomplish tasks more quickly	
Perceived complexity	PC1	The complicatedness of BDA adoption will result in a quality reduction in my bank	Abdekhoda *et al.* (2019)
	PC2	Due to some BDA adoption advantages, including lack of time and place limitations and ease of use, it is claimed to be better than its similar previous technologies	
	PC3	My bank believes that BDA is complicated to use	
	PC4	My bank believes that adopting BDA need much effort	
	PC5	Using BDA in my bank is often frustrating	
	PC6	Adopting BDA in my bank needs much mental effort	
Financial resources	FR1	Adopting BDA has high setup costs	Ilin *et al.* (2017)
	FR2	BDA has high running and training costs	
	FR3	BDA has high maintenance and disposal costs	
Bank size	BS1	The capital of my bank is high compared to the industry	Nguyen *et al.* (2022)
	BS2	The revenue of my bank is high compared to the industry	
	BS3	The number of employees at my bank is high compared to the industry	

Table A1.
Measurement items

(*continued*)

Construct	Item Code	Measurement items	Reference
Top Management Support	TMAS1	Top management is aware of the advantages that BDA can bring for future success to the bank	Abdekhoda *et al.* (2018), Ilin *et al.* (2017)
	TMAS2	Top management influences employees to increase awareness of the advantages that BDA can bring for the future success of the bank	
	TMAS3	BDA adoption enjoys top management support	
	TMAS4	Top management support results in more efficiency of BDA	
Perceived trend	PT1	At a country level, authorities encourage my bank to adopt BDA	Nguyen *et al.* (2022)
	PT2	Adopting BDA technologies is becoming a trend in digital transformation	
	PT3	More banks in our industry will adopt BDA in digital transformation	
Perceived intensity	PI1	Business partners recommended that my bank adopt BDA	Ilin *et al.* (2017)
	PI2	Business partners requested my bank to adopt BDA	
	PI3	The bank experienced competitive pressure to adopt BDA	
	PI4	The bank would have experienced a competitive disadvantage if BDA had not been adopted	
BDA adoption	BDA1	BDA adoption will simplify the analysis of clients' incomes and expenditures	Abdekhoda *et al.* (2018)
	BDA2	BDA adoption will simplify the segmentation of the customer base	
	BDA3	BDA adoption will simplify risk assessment and fraud prevention	

Note(s): Borrowed from various references as listed above

Table A1.

Corresponding author
Herman Mandari can be contacted at: mandariherman@gmail.com