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ANTECEDENTS OF BUSINESS ANALYTICS ADOPTION AND IMPACTS ON BANKS' PERFORMANCE: THE PERSPECTIVE OF THE TOE FRAMEWORK AND RESOURCE-BASED VIEW

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ABSTRACT

Aim/Purpose	This study utilized a comprehensive framework to investigate the adoption of Business Analytics (BA) and its effects on performance in commercial banks in Jordan. The framework integrated the Technological-Organizational-Environmental (TOE) model, the Diffusion of Innovation (DOI) theory, and the Resource-Based View (RBV).

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Background The recent trend of utilizing data for business operations and decision-making has positively impacted organizations. Business analytics (BA) is a leading technique that generates valuable insights from data. It has gained considerable attention from scholars and practitioners across various industries. However, guidance is lacking for organizations to implement BA effectively specific to their business contexts. This research aims to evaluate factors influencing BA adoption by Jordanian commercial banks and examine how its implementation impacts bank performance. The goal is to provide needed empirical evidence surrounding BA adoption and outcomes in the Jordanian banking sector.

Methodology The study gathered empirical data by conducting an online questionnaire survey with senior and middle managers from 13 commercial banks in Jordan. The participants were purposefully selected, and the questionnaire was designed based on relevant and well-established literature. A total of 307 valid questionnaires were collected and considered for data analysis.

Contribution This study makes a dual contribution to the BA domain. Firstly, it introduces a research model that comprehensively examines the factors that influence the adoption of BA. The proposed model integrates the TOE framework, DOI theory, and RBV theory. Combining these frameworks allows for a comprehensive examination of BA adoption in the banking industry. By analyzing the technological, organizational, and environmental factors through the TOE framework, understanding the diffusion process through the DOI theory, and assessing the role of resources and capabilities through the RBV theory, researchers and practitioners can better understand the complex dynamics involved. This integrated approach enables a more nuanced assessment of the factors that shape BA adoption and its subsequent impact on business performance within the banking industry. Secondly, it uncovers the effects of BA adoption on business performance. These noteworthy findings stem from a rigorous analysis of primary data collected from commercial banks in Jordan. By presenting a holistic model and delving into the implications for business performance, this research offers valuable insights to researchers and practitioners alike in the field of BA.

Findings The findings revealed that various technological (data quality, complexity, compatibility, relative advantage), organizational (top management support, organizational readiness), and environmental (external support) factors are crucial in shaping the decision to adopt BA. Furthermore, the study findings demonstrated a positive relationship between BA adoption and performance outcomes in Jordanian commercial banks.

Recommendations for Practitioners The findings suggest that Jordanian commercial banks should enforce data quality practices, provide clear standards, invest in data quality tools and technologies, and conduct regular data audits. Top management support is crucial for fostering a data-driven decision-making culture. Organizational readiness involves having the necessary resources and skilled personnel, as well as promoting continuous learning and improvement. Highlighting the benefits of BA helps overcome resistance to technological innovation and encourages adoption by demonstrating improved decision-making processes and operational efficiency. Furthermore, external support is crucial for banks to adopt Business Analytics (BA). Banks should partner with experienced vendors to gain expertise and incorporate best practices. Vendors also provide training and technical support to overcome technological barriers. Compatibility is essential for opti-

mal performance, requiring managers to modify workflows and IT infrastructure. Complexity, including data, organizational, and technical complexities, is a major obstacle to BA adoption. Banks should take a holistic approach, focusing on people, processes, and technology, and prioritize data quality and governance. Building a skilled team, fostering a data-driven culture, and investing in technology and infrastructure are essential.

Recommendations for Researchers	The integration of the TOE framework, the DOI theory, and the RBV theory can prove to be a powerful approach for comprehensively analyzing the various factors that influence BA adoption within the dynamic banking industry. Furthermore, this combined framework enables us to gain deeper insights into the subsequent impact of BA adoption on overall business performance.
Impact on Society	Examining the factors influencing BA adoption in the banking industry and its subsequent impact on business performance can have wide-ranging societal implications. It can promote data-driven decision-making, enhance customer experiences, strengthen fraud detection, foster financial inclusion, contribute to economic growth, and trigger discussions on ethical considerations.
Future Research	To further advance future research, there are several avenues to consider. One option is to broaden the scope by including a larger sample size, allowing for a more comprehensive analysis. Another possibility is to investigate the impact of BA adoption on various performance indicators beyond the ones already examined. Additionally, incorporating qualitative research methods would provide a more holistic understanding of the organizational dynamics and challenges associated with the adoption of BA in Jordanian commercial banks.

Keywords business analytics, technology adoption, banking, toe framework, data quality, diffusion of innovation, organizational readiness, business performance

INTRODUCTION

Business analytics (BA) has experienced a surge in popularity over the past decade, emerging as a major investment priority for organizations worldwide (Hayajneh et al., 2022). This growing emphasis on BA is primarily driven by the recognition that data holds immense value and can yield substantial business benefits when effectively processed (Hmoud et al., 2023). Organizations can now reveal hidden patterns, trends, and previously undiscovered correlations by leveraging the power of data for analytical purposes (Perdana, Lee, Koh, & Arisandi, 2022). BA allows organizations to delve deep into complex datasets and extract valuable insights that may have remained hidden using traditional analysis methods. Such capability to uncover hidden insights empowers them to make informed decisions, optimize their strategies, and drive meaningful business outcomes (Kristoffersen et al., 2021). In this regard, BA can substantially impact business performance, making it a crucial priority for decision-makers of organizations (Huang et al., 2022).

BA can be conceptualized as a systematic and iterative process that entails collecting, analyzing, utilizing, and interpreting data to acquire insightful knowledge that can be effectively used to create business value and achieve sustainable business performance (Chatterjee et al., 2022). Typically, the process of BA involves a sequential application of various analytical techniques, collectively referred to as descriptive, predictive, and prescriptive analytics (Schmitt, 2023). Descriptive analytics focuses on summarising and visualizing data to gain insights into previous occurrences and existing circumstances (Raghupathi & Raghupathi, 2021). On the other hand, predictive analytics utilizes statistical techniques and mathematical algorithms based on historical data to identify trends and patterns, enabling organizations to forecast future outcomes and anticipate potential opportunities or risks. Prescriptive analytics takes a step further by using optimization and simulation techniques to recommend the best course of action based on identified patterns and predicted outcomes.

The rise of BA can be attributed to several factors, including the increasing availability of data, advancements in technology, and the imperative for organizations to optimize their operations and adopt data-driven decision-making practices (Rana et al., 2022). Meanwhile, Chatterjee et al. (2022) point out that the business process is closely linked to modern technology, driven by innovative technologies such as BA. These technologies are deployed to connect multiple processes and obtain valuable, rare, inimitable, and non-substitutable (VRIN) resources, ultimately leading to improved business performance according to the concept of resource-based view (RBV) theory (Barney, 1991).

This era of technological innovation has particularly impacted various sectors, notably the banking industry (Pillay & van der Merwe, 2021). Banks currently face the challenge of managing vast amounts of financial and customer data. This complex endeavor is aptly tackled by utilizing BA, which involves classifying, processing, and interpreting data into meaningful insights using various techniques that delve into historical and current performance. In doing so, BA empowers bank managers to arrive at well-informed, accurate, timely, and relevant decisions (Bany Mohammad et al., 2022). This, in turn, leads to increased productivity, profitability, and the ability to comply with the diverse regulatory and environmental dimensions specific to this industry. Thus, BA emerges as an indispensable administrative instrument that facilitates an analysis of the dynamic business setting and fosters the decision-making process (Zheng & Khalid, 2022).

By embracing BA, banks will have a distinct opportunity to improve critical aspects of their operations, including customer information management, risk assessments, product offerings, and understanding market demand and expectations (Horani, Khatibi, AL-Soud, & Tham, 2023). For example, descriptive analytics allows banks to segment customer data into categories like frequent service usage, spending patterns, and complaints. That empowers banks to understand customer demands and trends, leading to refined marketing strategies that enhance customer satisfaction and experience across various touchpoints. Predictive analytics can also support banks with proactive strategies, such as offering tailored products and services aligned with customer preferences, evaluating loan applicant default risks, and identifying and preventing potential fraud. Such strategies can improve commercial banks' marketing and risk management performance (Hung et al., 2020; Nobanee et al., 2021). Finally, prescriptive analytics can aid banks in identifying the most influential branch locations based on demographics, competition, and customer behavior data while also facilitating the optimization of cash distribution across branches and ATMs, resulting in optimized branch networks and improvements in operational efficiency (Rahman, 2023).

Due to their significant business implications, the adoption of BA solutions is increasing among banks, primarily driven by the availability of large customer datasets (Bany Mohammad et al., 2022). These datasets play a crucial role in facilitating improved decision-making in the banking sector, enabling banks to meet customer expectations, allocate resources judiciously, and even rejuvenate their business models (Hajiheydari et al., 2021). In light of this, traditional banks might encounter difficulties competing against emerging entrants like FinTech companies (Kikan et al., 2019). These novel participants hold a significant competitive edge due to their ability to offer more precise projections, particularly within a volatile business environment.

The expansion of the BA environment has become increasingly significant, requiring practitioners and researchers to recognize its value and impact on business performance (Lutfi et al., 2023). However, the existing literature lacks satisfactory evidence regarding the factors that affect BA, and there are inconsistencies in the results (Bany Mohammad et al., 2022; Youssef et al., 2022). Concurrently, there have been discussions about whether BA can provide value and improve the performance of commercial banks in Jordan (Al-Dmour et al., 2023). Since the issue is underexplored, this study aims to address this gap by proposing and empirically testing a unified model for the adoption and impact of BA within the banking sector. To this end, this study intends to tackle the following questions:

RQ1: What factors affect the adoption of BA in Jordanian commercial banks?

RQ2: What are the implications of adopting BA on Jordanian commercial banks' performance?

In order to address these inquiries, this research initially reviewed the extant literature on the adoption of BA and its related concepts. Subsequently, a research model was developed based on the TOE framework, which allows for examining the factors that impact BA adoption. Next, the research model was tested by collecting data from 13 commercial banks in Jordan. The collected data was then analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The contribution of this study in the BA domain is twofold. Firstly, it presents a research model that captures the factors influencing the adoption of BA. Secondly, it sheds light on the impact of BA adoption on business performance. These findings are based on a robust analysis of primary evidence gathered from commercial banks in Jordan. By offering a holistic model and exploring the implications for business performance, this research provides valuable insights for both researchers and practitioners in the field of BA.

The remainder of the paper is structured as follows. First, an overview of BA literature and theoretical background is provided. Subsequently, the research model and hypotheses formulated through the TOE framework are presented. The applied research methodology is next discussed, followed by an elaboration of the data analysis process. The paper concludes with a discussion covering results, implications, limitations, and suggestions for future research.

LITERATURE REVIEW

BA involves the application of sophisticated analytical approaches, such as statistical techniques, mathematical models, and Artificial Intelligence (AI) algorithms, to extract meaningful insights from vast structured and unstructured datasets (Liu et al., 2023). In the existing literature, BA is frequently linked with related concepts, such as Big Data Analytics (BDA), Data Analytics (DA), and Business Intelligence (BI) (Alaskar, 2023; Horani, Khatibi, AL-Soud, Tham, & Al-Adwad, 2023; Perdana, Lee, Arisandi, & Koh, 2022). These interconnected concepts have captured the attention of scholars, leading them to delve deeper into identifying factors that propel organizations to adopt them. In light of this, there has been an ongoing and dedicated effort within academia and research to identify the driving forces that lead organizations to integrate BA seamlessly into their operational frameworks. For example, Horani, Khatibi, AL-Soud, Tham, and Al-Adwad (2023) conducted a systematic literature review to develop a research classification framework drawing upon the TOE factors. This framework illustrates the factors potentially influencing BA adoption in organizational contexts, aiming to facilitate the decision-making process for organizations seeking to adopt BA effectively.

Moreover, several studies have sought to identify factors contributing to BA adoption in organizational contexts by applying the TOE framework to the BA literature. Table 1 provides a summary of frequently utilized factors in these studies (these factors are described further in the research model and hypothesis development section).

Furthermore, a subset of these studies has explored the relationship between the adoption of BA and business performance. For example, Lutfi et al. (2023) conducted a study on BA adoption within the retail industry in Jordan. The findings of this research demonstrated that factors such as relative advantage, top management support, organizational readiness, and government regulations significantly influence the adoption of BA. The study's results also unveiled a robust and favorable correlation between BA adoption and business performance.

Table 1. Extracted TOE constructs through BA-related studies in peer-reviewed journals

References	**Technology**				**Organization**		**Environment**	
	Relative Advantage	Compatibility	Complexity	Data Quality	Top Management Support	Organizational Readiness	Competitive Pressure	External Support
Maroufkhani et al. (2023)		X	X		X	X	X	X
Al-Dmour et al. (2023)		X	X		X	X	X	
Lutfi et al. (2023)	X				X	X		
Chong and Lim (2022)		X	X	X	X	X	X	X
Jum'a et al. (2022)	X				X		X	
Lutfi, Alsyouf, et al. (2022)	X	X	X		X	X	X	
Truong (2022)	X	X	X	X	X	X		X
Jaradat et al. (2022)	X	X	X	X				
Bany Mohammad et al. (2022)				X	X		X	
Youssef et al. (2022)	X	X	X		X		X	X
Park and Kim (2021)	X	X	X	X	X			
Baig et al. (2021)	X	X	X		X	X	X	
Marchena Sekli and de la Vega (2021)		X	X	X	X	X	X	X
Alaskar et al. (2021)	X	X	X		X	X	X	
Chaurasia and Verma (2020)		X	X	X	X		X	
Maroufkhani et al. (2020)	X	X	X		X	X	X	X
Sun et al. (2020)	X				X		X	
Yadegaridehkordi et al. (2020)	X	X	X		X	X	X	X
Bhatiasevi and Naglis (2020)		X			X		X	X
Owusu (2020)	X	X	X			X	X	
Verma and Chaurasia (2019)	X	X	X	X	X		X	
Nam et al. (2019)				X	X		X	
Lai et al. (2018)	X		X	X	X	X	X	
Rouhani et al. (2018)	X		X			X	X	
Puklavec et al. (2014)	X			X	X	X		X
Gangwar (2018)	X	X	X	X	X		X	X
Totals	18	18	19	12	23	15	21	10

Similarly, Yadegaridehkordi et al. (2020) adopted the TOE framework to identify the key factors affecting BA adoption in the hotel industry in Malaysia, along with its implications for business performance. The study revealed that BA adoption is influenced by factors such as relative advantage, compatibility, top management support, organizational readiness, organization size, external pressure, external support, and security and privacy concerns. Furthermore, the study demonstrated a positive association between BA adoption and business performance.

Moreover, Marchena Sekli and de la Vega (2021) have employed the TOE framework to investigate the key factors influencing the adoption of BA within higher education institutions in Latin America and its subsequent impact on business performance. The study findings highlighted that BA adoption is significantly influenced by compatibility, data quality, external support, and a positive correlation between the adoption of BA and business performance. Maroufkhani et al. (2020) also utilized the TOE framework to explore the determinants of BA adoption in SMEs in Iran. These determinants include complexity, top management support, organizational readiness, external support, uncertainty and insecurity, trialability, and observability. The study further confirms the significant impact of BA adoption on financial and marketing performance.

THEORETICAL BACKGROUND

Theoretical background refers to existing research and knowledge in a specific field that provides a context for understanding a particular research study or phenomenon (Kivunja, 2018). It involves identifying relevant theories, models, and concepts previously tested and published in the field of the study. The following subsection provides the underpinning theories adopted as the theoretical lens for this study.

TECHNOLOGY–ORGANIZATION–ENVIRONMENT (TOE) FRAMEWORK

The TOE framework, which was proposed in 1990 by DePietro, Wiarda, and Fleischer (1990) and is commonly cited as "Tornatzky and Fleischer," aims to understand the adoption and implementation of technological innovations within an organization. According to the TOE framework, the adoption and diffusion of new technologies are influenced by three main contextual aspects: technology, organization, and environment (Figure 1).

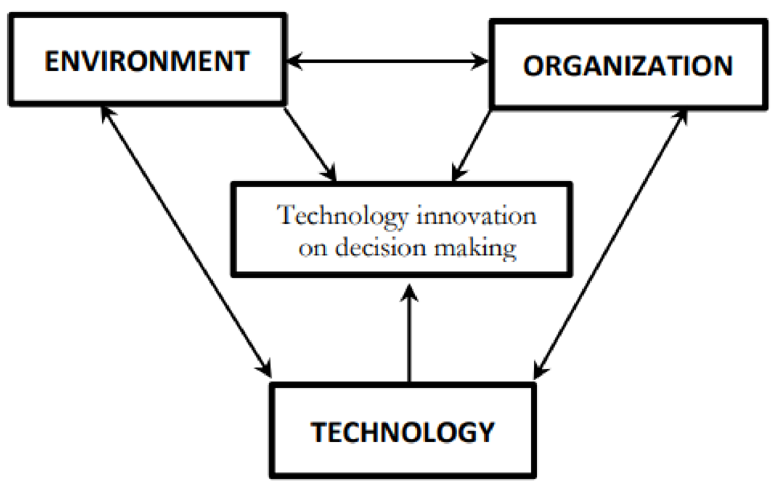

Figure 1. TOE framework adopted from DePietro et al. (1990)

The technological context explains all internal and external characteristics of innovative technology and its usefulness in the firm; the organizational context describes the organization's resources and characteristics that can impact the adoption decision; and the environmental context involves the arena in which a firm conducts its operations (DePietro et al., 1990).

The TOE framework suggests that the interaction between these three contexts determines the success or failure of technology adoption (DePietro et al., 1990). For example, a technology well-suited to an organization's needs and capabilities may fail if the external environment is not conducive to its adoption. Similarly, an organization may struggle to adopt a technology if it lacks the necessary resources or expertise to implement it effectively.

According to Ali et al. (2022) and Oliveira and Martins (2011), TOE is a well-established theoretical framework and has proven helpful when examining the organizational adoption and assimilation of various types of technologies as many empirical studies on innovative technologies have extensively proposed the TOE framework to identify the factors that may affect technology adoption in organizations, such as cloud computing (Yaseen et al., 2023), customer relationship management systems (Cruz-Jesus et al., 2019), e-commerce (Hoang et al., 2021), green innovation (Zhang et al., 2020), blockchain technology (Cunha et al., 2022), and artificial intelligence (Horani, Al-Adwan, et al., 2023). Furthermore, the theory is also applied in the BA context to structure the antecedents of BA adoption and provide an understanding of the impact of BA on business performance (e.g., Kalaitzi & Tsolakis, 2022; Ramanathan et al., 2017).

The studies above demonstrate the valuable insights the TOE framework offers into understanding the adoption of technological innovations across various industries and contexts. Therefore, given that the theme of this study is the adoption of innovative technology from the organization's perspective, the TOE framework serves as an overarching theoretical basis for the current study, driven by its consistency with other frameworks, such as the DOI theory (Badi et al., 2020; Oliveira & Martins, 2011), and RBV theory (Lutfi et al., 2023), as well as the most frequently-used technology adoption theory among scholars (Maroufkhani et al., 2020).

Diffusion of Innovation (DOI) Theory

DOI theory is one of the most popular theories for studying innovation/technology adoption and understanding how it spreads within societies (Nam et al., 2019). The theory was developed in 1971 by Everett M. Rogers in collaboration with F. Floyd Shoemaker (Rogers & Shoemaker, 1971).

According to Rogers (2003), innovation refers to an idea, process, or object that is perceived as new or unfamiliar to individuals within a specific social system. Diffusion occurs when information about an innovation spreads through communication channels over time, from one person to another within a social system. In this sense, diffusion takes place as enterprises, groups, individuals, or even countries adopt and implement innovative ideas or technologies.

According to Hsu et al. (2006), the DOI theory describes adoption patterns, explains diffusion mechanisms, and aids in predicting whether and how innovation will succeed. Moreover, DOI asserts that an organization's growth and capacity for innovation depend not only on technological capability but also on the collaborative process, the characteristics of its adopters, and the influence of its social class (Basloom et al., 2022). In addition to organizational characteristics, the DOI theory acknowledges individual characteristics that exist within the firm to explain innovation adoption. Thus, the adoption of innovation in organizations is influenced by three variables: individual characteristics, which describe leadership's attitude toward change determined by personal traits; internal characteristics of organizational structure, such as centralization, formalizations, and the number of employees; and external characteristics of the organization that refers to system openness as depicted in Figure 2.

Similar to the TOE framework, DOI theory has been utilized extensively in recent years in the field of information systems (IS) research, such as knowledge management systems usage (Okour et al., 2021), unified payment interface platforms adoption (Fahad & Shahid, 2022), blockchain technology adoption in the supply chain (Agi & Jha, 2022), and big data analytics adoption in business consulting services (Oyewo et al., 2022).

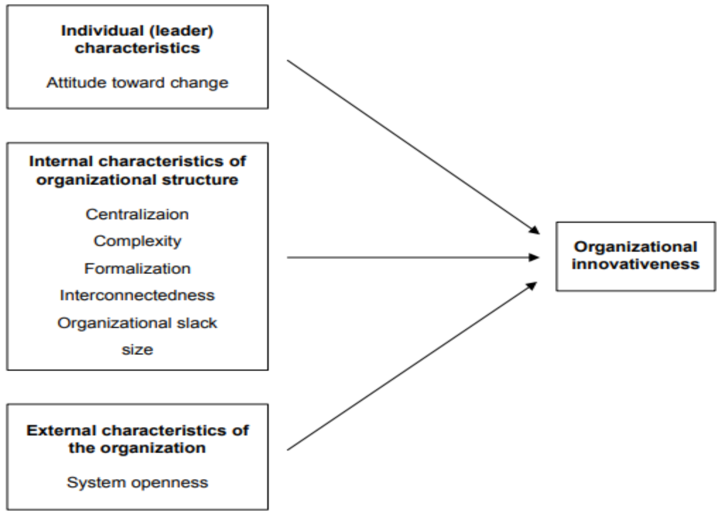

Figure 2. Diffusion of Innovation adopted from Rogers (2003)

Integrating TOE and DOI

In innovation technologies research, combining the TOE framework and DOI theory is well suited to understanding innovative technology adoption at the organizational level (Alaskar et al., 2021; Hsu et al., 2006; Oliveira & Martins, 2011). This pairing is grounded in the similarity between the technology and organization classifications in the TOE framework and DOI theory. However, the two theories have significant differences. For example, the DOI theory does not consider the influence of the environmental context. In contrast, the TOE framework does because it presents the firm's external conditions, such as competitors and dealing with the government. Furthermore, the DOI theory proposes the presence of individual characteristics (e.g., top management support) in the organizational context, but the TOE framework does not require that (Basloom et al., 2022).

Based on the discussion above, the TOE framework, coupled with the DOI theory, provides a useful theoretical framework for explaining the organization's adoption of innovation, as well as strong empirical support for the adoption of innovative research that accounts for technological, organizational, and external factors influencing on adoption among business organizations (Alaskar et al., 2021; Basloom et al., 2022; Oliveira et al., 2014). Therefore, combining the two theories enables the current study to examine the adoption of BA with independent variables developed based on technological, organizational, and environmental contexts.

Resource-Based View (RBV)

RBV has attracted significant interest in strategic management research as one of the most prominent theories used to explain how firms attain and sustain a competitive advantage by creating bundles of strategic resources or capabilities they own or under control (Barney et al., 2001; Mikalef et al., 2020; Zahra, 2021).

According to the RBV theory, a firm's performance is highly dependent on the qualities/characteristics of certain tangible and intangible resources or capabilities, such as information and knowledge, as well as the firm's routines and processes (Barney, 1991; Lutfi et al., 2023). Specifically, as the theory posits, the resources that are VIRN (i.e., valuable, inimitable, rare, and non-substitutable) can confer businesses a competitive advantage through value creation and optimize performance. These distinct resources possess characteristics, such as being economically valuable, relatively rare, difficult for rivals to replicate, and irreplaceable by other market participants. Consequently, a long-term advantage can be leveraged from such resources to the level a firm will safeguard resource transfer, substitute, or even imitate (Lutfi et al., 2023). This argument has encouraged scholars to apply the RBV in many business contexts to understand how technology contributes to creating business value that ultimately leads to improved business performance (Perdana, Lee, Koh, & Arisandi, 2022).

In the BA context, RBV contends that the capability of BA processing can lead to the attainment of competitiveness as data are increasingly regarded as a vital intangible resource or a means to improve the performance of businesses (Lutfi et al., 2023). Intangible resources are crucial in this regard since they can broaden the decision-maker's perspectives and increase their knowledge for making sound decisions (Maroufkhani et al., 2020). Therefore, BA can be regarded as a crucial capability for organizations, incorporating tools, techniques, and methods that empower them to process and analyze data, facilitating informed operational and strategic decision-making.

Accordingly, drawing upon previous research investigating the impact of BA adoption on firm performance (e.g., Aydiner et al., 2019; Chatterjee et al., 2021), the current study conceptualizes BA adoption as a capability in banks and is considered an intangible resource. The acquisition of new knowledge or skills leads the firm to possess a better technological capability, specifically BA capability, which thus leads to improved business performance (Chatterjee et al., 2021; Maroufkhani et al., 2020).

RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

To develop a parsimonious research model, we conducted an extensive literature search and identified eight constructs as determinants of organizational BA adoption (refer to Table 1). These constructs are highly relevant explanatory factors and were extracted through BA-related studies. Considering TOE as a base for the proposed research model, we categorized these constructs into technological, organizational, and environmental contexts as predictors of BA adoption. In addition, the proposed model investigates the relationship between BA adoption and bank performance, a common approach in the related literature (e.g., Al-Dmour et al., 2023; Lutfi et al., 2023; Yadegaridehkordi et al., 2020). However, it is essential to note that the process of organizational adoption pertains to various levels within an organization, such as business units, functional teams, or the organization as a whole (Premkumar & Ramamurthy, 1995). At an organizational level, innovation adoption can be represented in several ways, including the decision to adopt, the intent to adopt, the intent to use, and the actual usage of a novel technology (Jeyaraj et al., 2006). Accordingly, the current study, which focuses on BA adoption in Jordanian commercial banks, defines adoption as the actual use of BA. Figure 3 presents the proposed conceptual model of this study grounded in the TOE framework, DOI, and RBV theory.

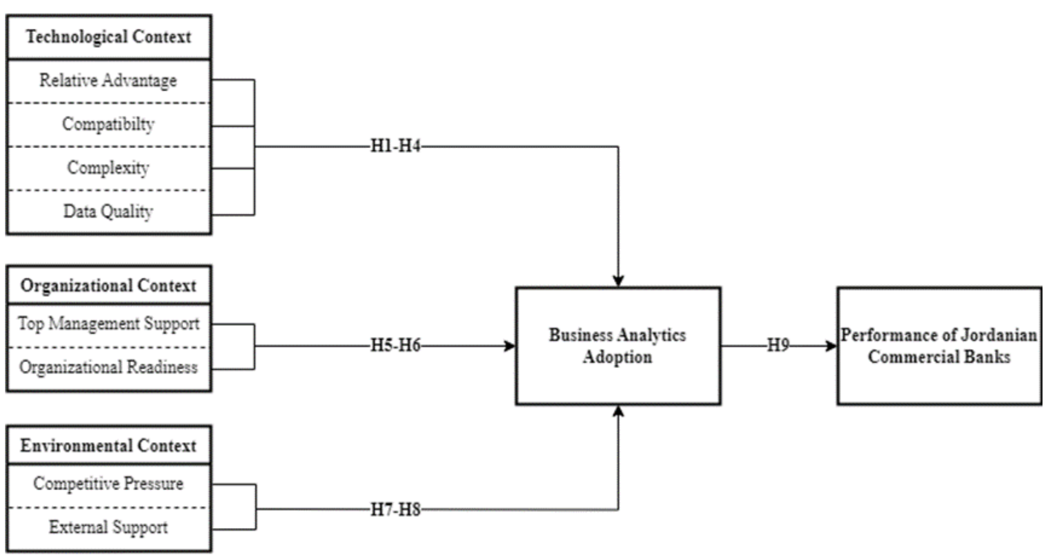

Figure 3. The proposed conceptual model

Technological Context

Technological context refers to the intrinsic characteristics of technology that can positively or negatively impact the adoption process (DePietro et al., 1990; Lai et al., 2018). In this context, Rogers (2003) identified five key technological characteristics that should be considered when making an adoption decision: relative advantage, compatibility, complexity, observability, and trialability. However, several studies have asserted that complexity, compatibility, and relative advantage are consistently identified as significant factors in adopting IT innovations (Alaskar et al., 2021; Gangwar, 2018; Verma & Chaurasia, 2019). Conversely, observability and trialability are associated with increased uncertainty concerning innovation and may not be deemed the most important characteristics by adopters.

In addition, recent studies have identified other factors within the technological context that are significant for technology adoption, particularly in the context of BA. For instance, Lai et al. (2018) have highlighted the importance of data quality, as data serves as the foundation of BA. Similarly, Nam et al. (2019) emphasize that data quality is a critical technological factor for BA adoption. It is also reported that poor data quality can result in poor decision-making, decreased customer satisfaction, increased operational costs, and lower organizational performance. In this study, relative advantage (REA), compatibility (COM), complexity (COX), and data quality (QUL) account for the technological factors relevant at the organizational level, as they have been widely addressed in the literature on BA adoption.

Relative advantage (REA)

While Rogers (2003) posits that innovation possesses certain characteristics that may impact its adoption, one such characteristic is a relative advantage, which pertains to the perception of the level to which an innovation offers superior benefits, related but not limited to economic and social prestige benefits, compared to its alternatives (Oyewo et al., 2022). An organization contemplating the adoption of technology will look at its potential advantages and how it will enhance efficiencies and augment the value of its operations (Ram et al., 2019). Several scholarly works contend that BA possesses unique attributes besides its organizational benefits (Lutfi et al., 2023; Maroufkhani et al., 2020). According to Oyewo et al. (2022), BA is favored over traditional data analysis methods because it offers extensive insights into organizational issues by analyzing large amounts of diverse data. This study suggests that commercial banks are inclined to adopt BA if they perceive its benefits surpass their current technology. Therefore, the following hypothesis is proposed for testing:

H1: Relative advantage positively influences BA adoption by Jordanian commercial banks.

Compatibility (COM)

In the realm of technology adoption, compatibility refers to the degree of correspondence between an innovation and an organization's current system, as well as the alignment of the technology with the organization's business practices and cultural norms (Lutfi, Alsyouf, et al., 2022). Incompatible innovations are likely to encounter low levels of adoption compared to compatible ones (Oyewo et al., 2022; Yadegaridehkordi et al., 2020). Moreover, Alaskar et al. (2021) emphasize that organizations can reap the benefits of IT innovation by ensuring compatibility with their existing systems.

Compatibility has been widely recognized in the literature as a crucial factor in technology adoption (Gangwar, 2018; Yadegaridehkordi et al., 2020). Meanwhile, studies within the BA context have confirmed the correlation between compatibility and BA adoption (Baig et al., 2021; Lutfi, Al-Khasawneh, et al., 2022; Maroufkhani et al., 2023). This study suggests that commercial banks are more inclined to accept and integrate BA adoption in various aspects of their operations if they perceive that it is aligned with their current systems, organizational procedures, and standards. Therefore, the following hypothesis is proposed for testing:

H2: Compatibility positively influences BA adoption by Jordanian commercial banks.

Complexity (COX)

Complexity refers to the level of difficulty associated with using a technology or system and its implementation challenges (Rogers, 2003). The complexity of innovation can impede its adoption as simpler technologies tend to be adopted more quickly (Gangwar, 2018; Maroufkhani et al., 2023; Oyewo et al., 2022). In terms of BA, the obstacles involved in its implementation, such as data security, privacy concerns, diversity of techniques, and time required to comprehend, negatively influence its adoption (Marchena Sekli & de la Vega, 2021; Verma & Chaurasia, 2019). This study suggests that commercial banks with a perception of high complexity in BA are less prone to its adoption. Therefore, the following hypothesis is proposed for testing:

H3: Complexity negatively influences BA adoption by Jordanian commercial banks.

Data quality (QUL)

In line with BA literature, data quality refers to the degree to which data used in analytics conforms to established standards, including accuracy, completeness, consistency, and relevance (Bany Mohammad et al., 2022). BA is characterized by its use of data from various sources, often resulting in diverse data formats (Marchena Sekli & de la Vega, 2021). This diversity in data formats presents a significant challenge in ensuring the compatibility and consistency of data for analysis (Puklavec et al., 2014). In this regard, properly cleaning and transforming the data is essential to ensure its high quality before leveraging it for insights and decision-making (Marchena Sekli & de la Vega, 2021; Nam et al., 2019).

Previous studies on BA adoption have emphasized that high data quality enhances the reliability and trustworthiness of data analysis results, thereby supporting informed decision-making by organizations (Chatterjee et al., 2021; Gangwar, 2018; Lai et al., 2018; Nam et al., 2019). Conversely, inadequate data quality can result in erroneous conclusions, resource misallocation, and diminished confidence in data-driven decision-making (Chaurasia & Verma, 2020). Meanwhile, Bany Mohammad et al. (2022) point out that ensuring data quality is a challenging and ongoing effort. This study suggests that commercial banks can foster greater confidence in successfully utilizing BA in their daily operations by having higher data quality. Therefore, the following hypothesis is proposed for testing:

H4: Data quality positively influences BA adoption by Jordanian commercial banks.

Organizational Context

The organizational context describes the characteristics and resources available within a firm that facilitate the adoption and use of innovation (Gangwar, 2018). Typically, the organizational context includes the management structure, the leadership's support for innovation, and the organization's size. In addition, the resources available to the organization also play a role, such as financial resources, technical infrastructure, knowledge, and expertise (Stjepić et al., 2021). While prior studies have identified multiple factors within this context, top management support (TOP) and organizational readiness (ORG) are considered the most significant determinants for innovation adoption (Chong & Lim, 2022). Meanwhile, these two factors have also been examined explicitly in the relevant literature on BA adoption (Lutfi et al., 2023; Maroufkhani et al., 2020).

Top management support (TOP)

In this study, 'top management support' pertains to the degree to which senior management comprehends the benefits or strategic value linked with BA and acknowledges its technological capabilities (Lutfi et al., 2023). Previous studies found that supportive top management drives the successful adoption of innovation (Lutfi, Al-Khasawneh, et al., 2022; Maroufkhani et al., 2020; Meet et al., 2022). Top management support is necessary to create a supportive atmosphere, allocate appropriate resources, accelerate the technology adoption process (Yadegaridehkordi et al., 2020), and encourage its adoption among employees (Lutfi et al., 2023). Concerning BA, several authors indicate that top management support is critical as it ensures the provision of adequate resources for the required data integration and architecture, as well as user coordination (Marchena Sekli & de la Vega, 2021; Verma & Chaurasia, 2019). This study suggests that the success of BA adoption in commercial banks is higher when top management participates actively in the overall adoption process. Therefore, the following hypothesis is proposed for testing:

H5: Top management support positively influences BA adoption by Jordanian commercial banks.

Organizational readiness (ORG)

Organizational readiness refers to the state of resources an organization possesses that it presents to adopt and effectively use technological innovation (Lutfi, Alsyouf, et al., 2022). According to Maroufkhani et al. (2023), this can be gauged based on several factors, including but not limited to sufficient financial resources and allocated budget for IT, the appropriate level of IT infrastructure, as well as the availability of skilled labor who can implement and use the technology effectively. The organization's available financial, technological, and human capital resources significantly influence its willingness to embark on any technological innovation (Yadegaridehkordi et al., 2020)

In the area of BA and big data, academic communities have a consensus that organizational readiness is a critical precedent (or prerequisite) for implementing BA (Lutfi, Alsyouf, et al., 2022; Maroufkhani et al., 2020). Meanwhile, relevant studies on BA adoption have consistently revealed organizational readiness as a significant determinant of the adoption process (Puklavec et al., 2014; Stjepić et al., 2021; Youssef et al., 2022). This study suggests that commercial banks can use and maintain BA effectively if they possess adequate financial resources, a robust technological infrastructure, and skilled personnel. Therefore, the following hypothesis is proposed for testing:

H6: Organizational readiness positively influences BA adoption by Jordanian commercial banks.

Environmental Context

Under the TOE framework, environmental context refers to the external factors and conditions in an organization's broader environment that surround and influence its business activities (DePietro et al., 1990; Stjepić et al., 2021). According to Maroufkhani et al. (2020), organizations are increasingly mindful of the dynamic external ecosystem to maintain their adaptiveness and reinforce their market position. Previous studies have considered various environmental factors when researching technology adoption, such as external support, competitive pressure, consumer behavior, and dealing with the government (Maroufkhani et al., 2023). These factors can serve a dual role, either facilitating or hindering a firm's decision to adopt technological innovation (Alaskar et al., 2021; Lai et al., 2018; Maroufkhani et al., 2023). Of these factors, researchers have considered competitive pressure (COM) and external support (ESU) as key antecedents in technology adoption, particularly in the field of BA (Chong & Lim, 2022; Gangwar, 2018; Stjepić et al., 2021).

Competitive pressure (COP)

Competitive pressure refers to the degree of pressure a company perceives from its industry rivals (Baig et al., 2021). This aspect is of utmost importance since it indicates the current status of technology use, which encourages organizations to adopt innovation (Alaskar et al., 2021).

The role of competitive pressure in technology adoption has been widely recognized in the literature (Gangwar, 2018). Organizations are more likely to adopt new technology when it strengthens their competitive position in the evolving marketplace. Maroufkhani et al. (2020) indicate that increased pressure to compete can lead to greater success in adopting innovation as firms may be more willing to invest in new technology to help them gain a competitive edge in the market. Similarly, Chong and Lim (2022) point out that organizations can increase competitive pressure on their peers by being early adopters of BA, which can expedite the process of innovation adoption. This study suggests that the growing prevalence of BA among rival organizations may create a perception that BA is necessary for success in the industry, leading commercial banks to view it as a strategic investment to maintain their competitive position. Therefore, the following hypothesis is proposed for testing:

H7: Competitive pressure positively influences BA adoption by Jordanian commercial banks.

External support (ESU)

External support refers to the support provided by a vendor or third party to encourage organizations to innovate and adopt technologies (Maroufkhani et al., 2023). Scholars have identified external support as a critical factor that can significantly impact the success of innovation and drive its adoption (Chong & Lim, 2022; Maroufkhani et al., 2020). According to Yadegaridehkordi et al. (2020), the availability of vendor support can generate a favorable attitude toward technology and propel organizations to adopt technological innovations. In other words, the support by vendors or third parties can provide organizations access to expertise and resources they may not have in-house, as well as familiarity with emerging trends and best practices in their industry.

Concerning BA, research suggests that external support can facilitate the development of the necessary capabilities for successful BA implementation (Marchena Sekli & de la Vega, 2021; Maroufkhani et al., 2020). Such support can come from specialized service providers, vendors, or open-source platforms and can include a range of aspects, such as technical assistance and personnel development (Chong & Lim, 2022; Gangwar, 2018). This study suggests that commercial banks with greater external support are more likely to adopt and implement BA successfully. Therefore, the following hypothesis is proposed for testing:

H8: External support positively influences BA adoption by Jordanian commercial banks.

BA ADOPTION AND BUSINESS PERFORMANCE

Generally, the adoption of innovation by organizations aims to enhance their effectiveness or business performance (Hult et al., 2004). Business performance is defined in this study as "the achievement of organizational goals related to profitability and growth in sales and market share, as well as the accomplishment of general firm strategic objectives" (Hult et al., 2004, p. 430). According to Božič and Dimovski (2019), innovative organizations exhibit a greater sensitivity to external opportunities and are inclined to exploit technological innovation proactively. Elevated levels of responsiveness and proactivity exhibited by these organizations facilitate the introduction of new products or services featuring enhanced or avant-garde attributes, thereby contributing to improved business performance in terms of revenue, profits, and market share.

The adoption of BA proves to be an effective tool in the digital environment for gaining business insights. Organizations can uncover correlations and patterns that provide valuable information for making informed decisions and strategic planning by analyzing diverse data sets. For this, BA can lead to a competitive edge over rival firms in the current evolved market (Chatterjee et al., 2021).

The availability of data, coupled with advanced analytics tools and techniques, can provide organizations with valuable insights into customer behavior, preferences, and trends (Lutfi et al., 2023). Such accurate analysis of appropriate data can help the organization introduce new products or services with advanced features that may satisfy the current market demand (Chatterjee et al., 2021; Lutfi et al., 2023). For example, organizations can use predictive analytics to anticipate changes in customer demand and adjust their production or marketing strategies, accordingly, allowing them to stay ahead of their competitors (Oesterreich et al., 2022).

The literature shows a link between BA and business performance in terms of increased business value and competitive advantage (Aydiner et al., 2019). For example, Lutfi et al. (2023) point out that the increasing adoption of analytics can afford a competitive edge for organizations owing to the asymmetric nature of the information. This perspective aligns with the RBV theory, which underscores the exclusive and non-substitutable tenets since the quality insights derived from BA are often unique and difficult to imitate, rendering it an essential tool for achieving an advantage over rivals (Chatterjee et al., 2021). Furthermore, Marchena Sekli and de la Vega (2021) suggest that the interdependence of various analytics capabilities (conceptualized as descriptive, predictive, and prescriptive analytics) is essential. This interdependence leads to better performance and creates a challenging model for competitors to imitate. Similarly, Oesterreich et al. (2022) argue that these BA concepts will likely provide different levels of competitive advantage.

Moreover, Kristoffersen et al. (2021) suggest that BA capabilities allow organizations to conduct in-depth analyses, which can help them gain a competitive advantage. BA capability, in this context, refers to an organization's ability to effectively utilize its data, technology, and skilled workforce to generate data-driven insights. Additionally, Aydiner et al. (2019) and Ramanathan et al. (2017) contend that the adoption of BA can significantly improve performance by aligning it with the business operations and objectives of the organization.

Accordingly, incorporating BA into a bank's decision-making processes can facilitate the identification of patterns, trends, and relationships within complex data. This capability enables commercial banks to become evidence-based problem-solving organizations (Aydiner et al., 2019). Research across healthcare, education, and business demonstrates that evidence-based problem-solving leads to improved outcomes (Chen et al., 2012). As such, BA is a valuable tool for creating impact and value in organizations by contributing to enhanced performance (Lutfi, Al-Khasawneh, et al., 2022). Therefore, this study posits the following hypothesis:

H9: BA adoption has a positive effect on bank performance.

METHODOLOGY

SAMPLE AND PROCEDURES

The population for this study consisted of 13 commercial banks operating in Jordan. These banks are selected based on their leading level of application of modern technology (e.g., BA) and significant contributions to the national economy (Al-Okaily et al., 2022; Bany Mohammad et al., 2022). However, it should be noted that not all banks have reached the same level of adoption and establishment of BA technology, with some still in the early stages (Bany Mohammad et al., 2022). The target respondents for this study are senior and middle managers in commercial banks, specifically those in the IT, financial, compliance, risk management, and marketing departments.

The rationale for selecting these managers is that they use BA for strategic, tactical, and operational decision-making, possess the requisite knowledge to provide accurate responses, and are best placed to complete the questionnaire (Al-Dmour et al., 2023; Al-Okaily et al., 2022). However, obtaining an accurate sampling frame was challenging due to the geographical spread of participants across the branches of the selected banks and reasons related to security and privacy. Although research has demonstrated that the absence of a comprehensive sampling frame may have limited the sample's representativeness and reduced the generalizability of the results (Bryman, 2016), a multiple-informant strategy is used to select diverse participants from different bank departments and roles to address this limitation. This approach is beneficial when the sampling frame is unclear or unavailable (Al-Okaily et al., 2022). Furthermore, it allows for collecting rich data from multiple perspectives and helps mitigate common source bias (Podsakoff et al., 2012). In addition, research has demonstrated that using multiple informants can enhance the validity and reliability of survey data in organizational research (Eby et al., 2008).

Therefore, the purposive sampling technique is utilized to ensure the selection of a diverse and representative sample (Azam et al., 2023). This technique enabled the researchers to target individuals with relevant knowledge and expertise related to the study's research questions (Palinkas et al., 2015).

The link to the questionnaire form was sent directly to the Chief Information Officers (CIOs) at each bank's headquarters. The CIOs were requested to distribute the questionnaire link to the intended target respondents within their respective banks. This method was chosen because CIOs primarily oversee IT management practices at their banks.

Accordingly, a total of 328 questionnaires were returned. However, 21 questionnaires were reported as incomplete, with more than 70% of the questions left unanswered. Therefore, these questionnaires were excluded from the analysis. As a result, a total of 307 questionnaires were qualified for the data analysis. Drawing on Kock and Hadaya (2018), the resulting sample for this study is deemed appropriate and adheres to the recommended standards for attaining adequate statistical power. These standards encompass a significance level of 5% and a minimum coefficient of determination (R^2) of 0.25.

Additionally, the commonly applied "10 times rule" found in similar studies utilizing PLS-SEM software was utilized to determine the minimum sample size required (Alkhwaldi et al., 2023; Hujran et al., 2023). This rule suggests that the minimum sample size should be ten times greater than the maximum number of paths leading to endogenous latent variables in the proposed research model. In the proposed model of this study, there were 9 paths leading to endogenous constructs. Consequently, the minimum sample size required would be 90. Such a condition was satisfied as the sample size obtained for this study was 307. (See Table 2 for demographic distribution of the sample).

Table 2. Sample profile (N=307)

Demographic		Frequency	Percentage
Gender	Male	185	60%
	Female	122	40%
Age (years)	Less than 30	51	17%
	30–40	157	51%
	41–50	67	22%
	Over 50	32	10%
Education	Undergraduate	245	80%
	Postgraduate	62	20%
Job Position	Manager (Business functions)	197	64%
	Manager (IT functions)	110	36%
Years of experience	Less than 2	48	16%
	2–5	117	38%
	6–10	97	32%
	Over 10	44	14%

Measures

The questionnaire consisted primarily of two main parts. Specifically, the demographic information was gathered from the participants in the first part, while the second part was meant to measure the research model's constructs. Particularly, the second section included a total of 39 measurement items (see Appendix) adopted from related literature and modified as required for the purpose and context of this study. A 5-point Likert scale, from "1=strongly agree" to "5= strongly disagree", was utilized to measure all items. Since the scope of this study was Jordan, the questionnaire form was offered in English and Arabic. The back-translation method was used to verify the precision of the translation procedure (Sperber et al., 1994). Additionally, we recruited a panel of four experts (comprising two academicians and two practitioners) to evaluate the face and content validity of the questionnaire. The panel unanimously concurred that the questionnaire was relevant, clear, and understandable. Nonetheless, the panel put forth a few recommendations to improve the clarity of certain items further. Although we adopted measurement items that had been previously validated, a pilot test on 70 participants was conducted to make sure that the adopted measurement items were reliable and valid. The results showed that all constructs had a satisfactory Cronbach's alpha value (>0.7) (Hair et al., 2019).

DATA ANALYSIS PROCESS

The obtained data were analyzed using the variance-based structural equation modeling (SEM) method, also known as partial least squares (PLS), utilizing the SmartPLS software version 4 (Ringle et al., 2022). PLS-SEM has become popular among researchers due to its flexibility in sample size and distribution requirements, distinguishing it from other techniques like covariance-based SEM (CB-SEM). Unlike CB-SEM, which relies on strict assumptions of multivariate normality, PLS-SEM can handle non-normal data and factor indeterminacy (Hair et al., 2019). Moreover, PLS-SEM offers advantages over CB-SEM by accommodating different measurement scales and addressing complex model structures (Hmoud et al., 2023).

For this study, PLS-SEM was preferred as the dataset did not conform to a normal distribution (Kock, 2016; Sharma, 2019). Following the recommended approach by Hair et al. (2019), the data analysis was conducted in two sequential phases: first, the measurement model was assessed to determine if the constructs in the study model were reliable and valid; second, the structural model was tested to evaluate the significance of the proposed research hypotheses.

MEASUREMENT MODEL

At this stage, the reliability and validity of the collected data were evaluated by employing the PLS path modeling algorithm for a series of tests. These tests aimed to assess the quality of the measurements and determine whether the model effectively explains and predicts the target constructs to achieve satisfactory results (Hair et al., 2019). In order to assess construct reliability, two tests were performed. Specifically, the values of Cronbach's alpha (α) and composite reliability for each construct were assessed. The CR and α values obtained for each construct, as presented in Table 3, were higher than 0.7, indicating that all constructs are internally consistent and reliable.

Furthermore, convergent validity was determined based on factor loadings and the "average variance explained" (AVE) metrics. The results indicate that all measurement items have a factor loading exceeding 0.708, demonstrating that each measurement item adequately loads onto its intended theoretical construct (Table 3). Additionally, the AVE values for each construct are higher than 0.5, signifying the presence of convergent validity (Hair et al., 2019).

Table 3. Construct reliability and validity

Construct	Item	Loadings	Cronbach's Alpha	Composite Reliability	AVE
BA Adoption	BA1	0.928	0.899	0.937	0.831
	BA2	0.906			
	BA3	0.902			
Top Management Support	TOP1	0.875	0.893	0.925	0.756
	TOP2	0.860			
	TOP3	0.877			
	TOP4	0.866			

Construct	Item	Loadings	Cronbach's Alpha	Composite Reliability	AVE
Relative Advantage	REA1	0.892	0.853	0.910	0.772
	REA2	0.881			
	REA3	0.862			
	REA4*	0.523			
Organization Readiness	ORG1	0.861	0.880	0.917	0.735
	ORG2	0.869			
	ORG3	0.837			
	ORG4	0.862			
Compatibility	COM1	0.894	0.838	0.903	0.756
	COM2	0.842			
	COM3	0.871			
	COM4*	0.562			
Complexity	COX1	0.865	0.863	0.907	0.708
	COX2	0.808			
	COX3	0.856			
	COX4	0.838			
Data Quality	QUL1	0.902	0.916	0.941	0.799
	QUL2	0.897			
	QUL3	0.887			
	QUL4	0.890			
Performance	PER1	0.911	0.922	0.945	0.810
	PER2	0.899			
	PER3	0.896			
	PER4	0.894			
External Support	ESU1	0.887	0.899	0.929	0.760
	ESU2	0.857			
	ESU3	0.890			
	ESU4	0.869			
Competitive Pressure	COP1	0.852	0.859	0.905	0.704
	COP2	0.818			
	COP3	0.886			
	COP4	0.796			

* Item deleted

The last evaluation in this stage was the discriminant validity assessment. Two tests were conducted: (1) the Fornell-Larcker criterion (Fornell & Larcker, 1981); and (2) the HTMT test "heterotrait-monotrait ratio of correlations" (Henseler et al., 2015). The results in Table 4 indicate that the value of $\sqrt{AVE}$ for each construct was higher than the correlations involving the construct, and all HTMT values were below 0.85. Such results designate that the discriminant validity is present.

Table 4. Discriminant validity

	BA	COX	TOP	REA	ORG	COM	QUL	PER	ESU	COP
BA	**0.912**	0.784	0.737	0.789	0.726	0.725	0.762	0.739	0.697	0.648
COX	-0.692	**0.842**	0.710	0.829	0.647	0.694	0.762	0.833	0.602	0.599
TOP	0.662	-0.624	**0.870**	0.718	0.708	0.660	0.685	0.748	0.672	0.605
REA	0.692	-0.713	0.627	**0.879**	0.682	0.697	0.761	0.693	0.627	0.666
ORG	0.647	-0.565	0.627	0.591	**0.857**	0.640	0.684	0.680	0.671	0.641
COM	0.631	-0.592	0.572	0.589	0.549	**0.869**	0.665	0.690	0.640	0.581
QUL	0.692	-0.678	0.622	0.673	0.615	0.583	**0.894**	0.711	0.665	0.645
PER	0.674	-0.745	0.679	0.616	0.612	0.610	0.654	**0.900**	0.679	0.608
ESU	0.626	-0.530	0.603	0.549	0.596	0.557	0.604	0.619	**0.876**	0.588
COP	0.570	-0.515	0.531	0.568	0.557	0.494	0.571	0.539	0.515	**0.839**

Note: Numbers (in bold) on the leading diagonal are the $\sqrt{\text{AVE}}$ for each construct, HTMT values are above the main diagonal), and the correlation among the constructs is below the main diagonal.

Structural Model

Upon ascertaining that the measurement model is statistically reliable and valid, the subsequent phase in the implementation of PLS-SEM involves the evaluation of the structural model. At this stage, multicollinearity issues were initially investigated before examining the research hypotheses, as suggested by Hair et al. (2019). In order to identify multicollinearity, researchers commonly rely on two fundamental metrics, namely the variance inflation factor (VIF) and the tolerance (Daoud, 2017). Nevertheless, the current study focuses on utilizing VIF as the primary method for discerning multicollinearity to avoid redundancy. Ideally, the VIF values should be around (3 or less), as this confirms the absence of multicollinearity issues (Benitez et al., 2020). In doing so, the current study utilized the PLS algorithm to test the VIF values for collinearity among all the constructs in the study, as presented in Table 5.

Table 5. Multicollinearity test

Structural Relationship	**VIF**
BA -> PER	1.000
COM -> BA	1.957
COP -> BA	1.797
COX -> BA	2.582
QUL -> BA	2.599
ESU -> BA	2.028
ORG -> BA	2.181
REA -> BA	2.659
TOP -> BA	2.323

As shown in Table 5, all the independent variables possessed a VIF value less than 3, proving that multi-collinearity is not a concern in this study. The next step involves an examination of the structural model to determine the significance of the path coefficients (hypotheses) posited in the study model. Table 6 shows that all hypotheses were supported except for H7.

Table 6. Hypotheses testing

Hypotheses	Path	β	Mean	St Dev	T Statistics	Confidence Intervals	P Values	Assumption
H1	REA→BA	0.150	0.154	0.058	2.595	0.043, 0.27	0.009	Supported
H2	COM→BA	0.122	0.121	0.041	2.964	0.040, 0.202	0.003	Supported
H3	COX→BA	-0.178	-0.175	0.053	3.379	-0.279, -0.073	0.001	Supported
H4	QUL→BA	0.146	0.144	0.058	2.510	0.034, 0.26	0.012	Supported
H5	TOP→BA	0.115	0.114	0.048	2.409	0.021, 0.209	0.016	Supported
H6	ORG→BA	0.125	0.126	0.046	2.738	0.033, 0.212	0.006	Supported
H7	COP→BA	0.057	0.058	0.036	1.567	-0.012, 0.129	0.117	Not Supported
H8	ESU→BA	0.120	0.122	0.045	2.659	0.036, 0.212	0.008	Supported
H9	BA→PER	0.674	0.675	0.029	22.953	0.616, 0.731	0.000	Supported

In the context of technology, this study proposes that REA, COM, and QUL positively influence the adoption of BA among Jordanian commercial banks. Conversely, COX has a negative effect on BA adoption. The results in Table 6 indicate that REA (β=0.150, $p < 0.01$), COM (β=0.122, $p < 0.01$), and QUL (β=0.146, $p < 0.05$) significantly and positively affect BA adoption, thereby supporting hypotheses H1, H2, and H4. Additionally, the findings demonstrate that COX significantly and negatively impacts BA adoption (β=-0.178, $p < 0.01$), thus supporting H3. Concerning the organizational context, hypotheses 5 and 6 propose that TOP and ORG factors positively influence BA adoption. As shown above, the path from TOP to BA adoption is significant (β=0.115, $p < 0.05$), as well as the path from ORG to BA adoption (β=−0.125, $p < 0.01$). Therefore, these findings support the hypotheses mentioned above.

Regarding the environmental context, Hypotheses 7 and 8 state that COP and ESU factors positively influence the adoption of BA. Surprisingly, the path from COP to BA adoption was found to be insignificant (β=0.057, $p > 0.05$), while the path from ESU to BA adoption was significant (β=0.120, $p <0.01$). Hence, the results support Hypothesis 8 but not Hypothesis 7. Finally, the study proposes that BA adoption positively influences bank performance (PER). The results demonstrate that the effect of BA adoption on PER was found to be substantially significant and positive (β=0.674, $p < 0.001$), thus supporting H9.

The final step in the evaluation process was to assess the explanatory power of the study model. This was done by examining the coefficient of determination (R^2) and effect size (f^2) to evaluate how much variance in the dependent variable is explained by the independent variables. The predictive relevance (Q^2) was also analyzed to determine the model's predictive accuracy (Table 7).

As shown in Table 7, BA explained 45.5% of the total variance in PER (R^2=0.455). TOP, REA, COX, ORG, COM, QUL, ESU, and COP collectively explained 67% of the total variance in BA (R^2=0.67). Such explanatory power is considered moderate (Chin, 1998). Additionally, the research model has adequate predictive relevance as all Q^2 value for BA and PER was substantial >0 (Hair et al., 2019). The effect size (f^2) for the dependent variables was varied. The effect size (f^2) on BA on PER was substantially large, while the effect sizes of TOP, REA, COX, ORG, COM, QUL, and ESU were small.

Table 7. Explanatory power and predictive relevancy

	R^2	Q^2	f^2
BA	0.670	0.549	0.833
PER	0.455	0.364	-
COX			0.037
TOP			0.017
REA			0.026
ORG			0.022
COM			0.023
QUL			0.025
ESU			0.022
COP			0.005

f^2 values of 0.02, 0.15, and 0.35 are recognized as weak, medium, or large, respectively (Henseler et al., 2015).

INDIRECT EFFECT EVALUATION

While several PLS path models include mediation effects, these effects are often not explicitly hypothesized and tested (Hair et al., 2021). That means researchers may miss essential insights into the cause-effect relationships they are investigating. In order to address this gap, the current study also examines the potential mediation of BA adoption to gain a deeper understanding of its impact on business performance. Traditionally, the Sobel (1982) test was commonly used to assess the significance of mediating effects. However, it is now suggested that researchers switch to using bootstrapping to derive the sampling distribution of the indirect effect (Preacher & Hayes, 2008) due to its ability to yield higher statistical levels than the Sobel test (Zhao et al., 2010). Hence, this approach is well-suited for the PLS-SEM method (Hair et al., 2021).

As shown in Table 8, the empirical testing of the mediation effect in the PLS path model revealed several significant indirect effects on business performance through BA adoption. ESU, QUL, ORG, COM, TOP, and REA all had positive and significant indirect effects, implying that these factors significantly enhanced PER by facilitating BA adoption. However, COX exhibited a negative and significant indirect effect on PER through BA adoption, suggesting that higher complexity can impede PER by hindering the adoption of BA. On the other hand, the indirect effect of COP on PER through BA adoption was insignificant, indicating that COP did not play a significant role in boosting PER through increased BA adoption.

Table 8. Indirect effect evaluation

Path	β	Mean	STDEV	T Statistics	P Values
COP→BA→PER	0.038	0.039	0.025	1.557	0.119
ESU→BA→PER	0.081	0.082	0.031	2.604	0.009
QUL→BA→PER	0.098	0.097	0.039	2.491	0.013
ORG→BA→PER	0.084	0.085	0.031	2.717	0.007
COM→BA→PER	0.082	0.082	0.028	2.939	0.003
COX→BA→PER	-0.120	-0.119	0.037	3.264	0.001
TOP→BA→PER	0.078	0.077	0.032	2.395	0.017
REA→BA→PER	0.101	0.104	0.039	2.611	0.009

DISCUSSION

Regarding technological factors, the findings reveal that REA (H1) has a most favorable influence on BA adoption by Jordanian commercial banks. This result is consistent with previous research (e.g., Jaradat et al., 2022; Lutfi et al., 2023; Sun et al., 2020; Truong, 2022). However, other studies have reported inconsistent findings (Jum'a et al., 2022; Maroufkhani et al., 2020; Puklavec et al., 2014; Youssef et al., 2022). Such a finding implies that the BA adoption by banks can provide them with valuable insights into patterns and trends in data, which can lead to better decision-making, improved customer experience, identification of opportunities based on customer needs, and more effective risk management. The positive relationship between COM and BA adoption (H2) is also confirmed, which confirms previous BA studies (e.g., Al-Dmour et al., 2023; Marchena Sekli & de la Vega, 2021), while other research contradicts this finding (Chaurasia & Verma, 2020; Lutfi, Al-Khasawneh, et al., 2022; Verma & Chaurasia, 2019; Youssef et al., 2022). This finding suggests Jordanian commercial banks embrace technological innovation like BA when it is seamlessly well-matched with their current systems and workflows. The negative impact of COX on BA adoption (H3) in banks was also observed, which is consistent with the findings of Al-Dmour et al. (2023) and Maroufkhani et al. (2023). This finding may be attributed to the complex nature of BA, which involves working with large and diverse data sets, utilizing various analytical techniques, specialized software, and tools, and requires extensive collaboration across departments and teams. The results also emphasize QUL (H4) as the second most significant factor for BA adoption in Jordanian commercial banks. Previous studies have established a positive correlation between the quality of data and BA adoption (e.g., Bany Mohammad et al., 2022; Gangwar, 2018; Nam et al., 2019; Park & Kim, 2021). Conversely, findings by Lai et al. (2018) and Puklavec et al. (2014) show an insignificant relationship between these two variables. This finding proposes that effective decision-making is critical to achieving business success, and high-quality data is pivotal in facilitating this process. Additionally, accessing accurate, complete, timely, and relevant data enables managers to fully understand the decision-making context, which leads to enhanced decision-making productivity. Poor data quality, on the other hand, may impede the adoption of BA initiatives by yielding inaccurate or incomplete insights, resulting in unreliable decisions.

Concerning the organizational factors in this study, it is found that TOP and ORG positively influence BA adoption, demonstrating that (H5) and (H6) are supported. These expected findings are aligned with a plethora of literature that has identified TOP and ORG as recurring and essential elements for the successful adoption of BA (Chong & Lim, 2022; Lutfi et al., 2023; Maroufkhani et al., 2020; Truong, 2022; Yadegaridehkordi et al., 2020). Indeed, the role of top managers in creating a supportive organizational environment and allocating resources is critical to the successful adoption of BA. In contrast, inadequate financial resources, a lack of IT infrastructure, and an unskilled workforce can all hinder the adoption of BA among organizations.

In terms of environmental factors, the findings demonstrate that ESU (H8) has a positive effect on BA adoption in Jordanian commercial banks. While this finding is similar to those reported in previous studies (Chong & Lim, 2022; Marchena Sekli & de la Vega, 2021; Maroufkhani et al., 2020; Youssef et al., 2022), it is inconsistent with other studies (e.g., Bhatiasevi & Naglis, 2020; Puklavec et al., 2014). Support from vendors is vital in providing banks with the necessary resources to successfully adopt BA and overcome challenges such as a shortage of internal expertise and data silos. Contrary to previous research (Bany Mohammad et al., 2022; Owusu, 2020), COP (H7) did not exhibit a positive relationship with BA adoption in Jordanian commercial banks. This finding concurred with the work of Marchena Sekli and de la Vega (2021) and Maroufkhani et al. (2020). One possible explanation is that banks already have a wealth of data and analytics capabilities due to the nature of the banking industry and the services provided. Banks have been collecting and analyzing data for years, and many have developed in-house data analytics capabilities. However, it is still imperative for banks to consistently invest in upgrading their data and analytics capabilities. The banking industry is experiencing rapid digitization, and Jordanian commercial banks need to adapt their analytics to emerging technologies and ever-evolving customer needs and market conditions. Failing to do so risks their competitive position in the long run.

Finally, the findings support a positive association between BA adoption and PER (H9), which is in line with RBV theory and the results of the relevant literature (Chong & Lim, 2022; Lutfi et al., 2023; Marchena Sekli & de la Vega, 2021; Maroufkhani et al., 2020; Yadegaridehkordi et al., 2020). One possible explanation could be that BA adoption can enhance bank performance by improving the skills and knowledge of its managers and employees alike. BA tools provide managers with data-driven insights that enable informed decision-making, identification of key performance indicators, and early detection of potential issues, resulting in improved outcomes and performance.

IMPLICATIONS

The adoption of business analytics (BA) has been recognized as a critical factor for enhancing organizational performance. However, the literature on BA adoption has primarily focused on identifying factors that influence its adoption, and less attention has been paid to the mechanisms through which it affects business performance, particularly in the banking sector. The existing literature gap in this area was addressed in this study by combining the TOE framework, DOI, and the RBV theory, allowing for an examination of the factors influencing BA adoption and its subsequent impact on the performance of the banking industry. Particularly, this study investigated the influence of TOE factors on the adoption of BA in the banking industry within the Jordanian context. It contributes to the existing literature by proposing an integrated study model that combines TOE and DOI factors to understand their impact on BA adoption. The study findings revealed that COX, TOP, REA, ORG, COM, QUL, and ESU significantly influenced BA adoption in the banking industry. However, the study did not find a significant effect of COP on BA adoption. The results of this study present contrasting findings compared to previous research, which can be attributed to the nature of the organization under examination. Previous studies have primarily focused on manufacturing, higher education, and retail firms, thereby supporting the argument that the determinants of BA adoption in the bank industry are distinct from those applicable to other industries. Building upon the fundamental assumptions of RBV theory, this study highlights the crucial importance of harnessing BA as a valuable resource that contributes to firm value creation. The empirical findings of this study strongly support the notion that the adoption of BA positively influences firm value, with a particular emphasis on TOE factors. These factors have consistently demonstrated their significant impact on adoption patterns and subsequent firm performance outcomes.

From a practical perspective, the findings discussed above have various practical implications that can be applied to enhance BA adoption and its potential impact on banks' performance. This study revealed that data quality is the key facilitator of BA adoption. Hence, banks are expected to employ various steps to enforce data quality practices. Accordingly, banks are required to provide clear and steady data quality standards, which should be shared with all employees working with data. Investing in data quality tools and technologies, as well as conducting regular data audits, are considered crucial. These processes aid banks in identifying and rectifying data issues while also ensuring strict adherence to data quality standards. The findings also highlighted the importance of top management support on BA adoption. Thus, banks' top management can primarily facilitate BA adoption by fostering a cultural shift towards data-driven decision-making. When top management is supportive of BA, it signals to the rest of the organization that data-driven decision-making is a priority and that analytics is a valuable tool for achieving business goals.

Organizational readiness is identified as a vital factor facilitating BA adoption. Readiness can manifest by having necessary resources like funds, infrastructure, and analytics software/hardware to support capabilities. Moreover, having skilled personnel like data analysts and scientists to interpret and analyze data indicates fundamental readiness. Importantly, establishing a continuous learning and improvement culture is essential in banks aiming to leverage BA. This process involves investing in training programs to ensure employees and decision-makers develop skills to apply analytics tools effectively. The relative advantage factor is found to be another enabler of BA adoption. By highlighting the benefits of BA, banks can overcome the reluctance of employees and decision-makers to adopt technological innovation and pave the way for its successful implementation. Particularly, when the relative advantage of BA is clearly introduced, banks' employees are inclined to realize the benefits of adopting such technology and become keen to learn and use it in their work. As a result, banks can demonstrate the relative advantages of BA by presenting how it can improve decision-making processes and surge operational efficiency.

External support is recognized as a crucial determinant facilitating BA adoption within Banks. Through engaging with experienced vendors, banks can leverage their competencies and assimilate best practices to enhance their proficiency in BA adoption. To this end, banks must seek strategic partnerships with BA vendors that possess the requisite expertise to implement BA technologies effectively. Furthermore, banks must recognize BA vendors' pivotal role in delivering efficacious training programs and providing technical support, which mitigates technological barriers associated with BA adoption. The positive influence of compatibility suggests that the optimal performance of banks' IT infrastructure, work operations, applications, and processes require ensuring that BA has a beneficial impact. Consequently, managers have an obligation to undertake initiatives aimed at re-evaluating and modifying workflow and enhancing the IT infrastructure in a manner that meets the compatibility requirements of BA. Furthermore, managers should take into account that the BA adoption must conform to the banks' policies and IT development strategies.

Complexity is regarded as a primary inhibitor of BA adoption in banks. The complexity of implementing BA can hinder its adoption in banks in several ways. These include data, organizational, and technical complexity associated with BA implementation. Accordingly, banks should follow a holistic approach that focuses on people, processes, and technology. Such a holistic approach requires banks first to clearly identify businesses or opportunities that can be addressed using BA. This will guide banks to focus on the right data, analytics tools, and resources. Additionally, it is essential that banks prioritize data quality and governance in order to ensure that their analytics solutions are based on accurate and reliable data. The successful and smooth implementation of BA solutions requires banks to build a strong team with a combination of technical, business, and domain expertise. Finally, banks must prioritize the creation of a data-driven culture and invest in appropriate technology and infrastructure to support analytics initiatives.

CONCLUSION AND FUTURE RESEARCH

This study employed an integrated framework that combined the Technological-Organizational-Environmental (TOE) model, the Diffusion of Innovation (DOI) theory, and the Resource-Based View (RBV) to examine BA adoption and its impact on performance in Jordanian commercial banks. The study shed light on the TOE factors influencing BA adoption within this context through a comprehensive analysis of data collected from a sample of Jordanian commercial banks. The first research question was concerned with identifying the primary factors influencing the adoption of Business Analytics (BA) in Jordanian commercial banks. The findings highlight the significant influence of factors such as relative advantages (REA), compatibility (COM), complexity (COX), data quality (QUL), top management support (TOP), organizational readiness (ORG), and external support (ESU) on BA adoption in Jordanian commercial banks. Notably, REA emerges as the most influential factor, indicating that managers in Jordanian commercial banks perceive BA adoption as beneficial to their respective banks. This perception strongly supports the notion that adopting BA is a worthwhile investment. In addition, the results reveal a significant negative effect of COX on BA adoption, suggesting that the intricate nature of BA may act as a barrier for these banks. Unpredictably, the effect of competitive pressure (COP) was found to be statistically insignificant, suggesting that the role of competitive advantage may not be considered significant by these banks when contemplating the adoption of BA.

The second research question concerned whether the adoption of BA by Jordanian commercial banks would impact their performance. The study findings demonstrated the positive impact of BA adoption on the performance of banks. This finding emphasizes the value and relevance of incorporating BA into the strategic initiatives of Jordanian commercial banks, as it contributes to improved overall performance and competitiveness in the industry.

The study contributes to the existing literature by integrating multiple theoretical frameworks and examining their applicability in the Jordanian context. The findings provide valuable insights for practitioners and decision-makers in commercial banks in Jordan, highlighting the importance of considering technological, organizational, and environmental factors in the adoption and implementation of BA. By embracing BA, banks can harness the potential of data-driven decision-making, ultimately leading to improved performance and competitiveness in the dynamic banking industry.

While this study significantly contributes to the literature on BA adoption, certain limitations should be considered for future research endeavors. First, the theoretical model in this study was proposed based on the TOE framework, DOI, and RBV theories. While these frameworks provide a solid foundation for understanding the adoption of BA at the organizational level, future studies could explore alternative theoretical lenses, particularly at the individual level, to enrich a more in-depth understanding of BA adoption and its value for business. Second, although the current study adopted a deductive approach, future research on BA adoption should incorporate inductive research methods, particularly in the banking industry. By doing so, supplementary constructs can be identified and explored through in-depth qualitative analysis (Al-Adwan & Berger, 2015; Al-Adwan & Khdour, 2020), providing a deeper understanding of the organizational drivers and challenges associated with BA adoption. Third, the proposed theoretical model in this study aimed to investigate the influence of independent variables on BA adoption and the implication of BA adoption on business performance. Future research could investigate the impact of BA adoption on additional performance indicators, which would provide a broader understanding of the effects of BA adoption. Finally, the findings of this study may have limited generalizability due to the specific study scope focused on the commercial banking sector in Jordan. Therefore, caution should be exercised when applying these results to other counterparts in the industry. In this regard, future research could expand the scope by studying other counterparts within the banking industry or comparing the study results with those of developed countries.

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APPENDIX. QUESTIONNAIRE FORM

Construct	Measurement items	Source
Technological context		
Relative Advantage		
REA1	"Using BA allows our bank to avoid unnecessary costs and time-saving."	Jaradat et al. (2022); Stjepić et al. (2021
REA2	"Using BA makes it easier to perform business tasks."	
REA3	"The use of BA allows for greater control over the business."	
REA4	"The use of BA enables faster execution of actions and decision-making."	
Compatibility		
COM1	"BA is consistent with the current practices of our bank."	Lutfi et al. (2023); Marchena Sekli & De La Vega (2021); Baig et al. (2021)
COM2	"BA usage fits our organizational culture."	
COM3	"BA is compatible with the existing bank's IT infrastructure."	
COM4	"BA is compatible with the bank's current values and goals."	
Complexity		
COX1	"The process of getting acquainted with the work of BA is complex."	Maroufkhani et al. (2023); Stjepić et al. (2021); Baig et al. (2021)
COX2	"Using BA is complex and demanding for users."	
COX3	"BA is difficult to implement."	
COX4	"BA is difficult to maintain."	
Data Quality		
QUL1	"The data used in BA is in a clear format and conforms to industry standards."	Chong & Lim (2022); Stjepić et al. (2021); Puklavec et al. (2014)
QUL2	"The data that we currently use in our bank is reliable."	
QUL3	"A common definition of the main data source that can be mined is being applied in our bank."	
QUL4	"All data (account details, customer complaints, service inquiries, etc.) are managed similarly throughout our bank."	
Organisational context		
Top Management Support		
TOP1	"Our top management supports the implementation and adoption of BA."	Baig et al. (2021); Stjepić et al. (2021)
TOP2	"Our top management actively engages in developing a vision and formulating strategies to leverage BA effectively."	
TOP3	"Our top management believes that investment and expenditure in BA is worthwhile."	
TOP4	"Our top management is well prepared to undertake the possible risks associated with adopting and using BA."	

Construct	Measurement items	Source
Organization Readiness		
ORG1*	"Lacking financial resources has prevented our bank from fully exploiting BA."	Lutfi et al. (2023); Chong & Lim (2022); Maroufkhani et al. (2023); Yadegaridehkordi et al. (2020)
ORG2*	"Lacking the necessary technological resources has prevented our bank from fully harnessing the potential of BA."	
ORG3*	"Lacking skilled resources has prevented our bank from fully exploiting BA."	
ORG4	"Our bank has no difficulties finding all the necessary resources to exploit BA fully."	
Environmental context		
Competitive Pressure		
COP1	"Our bank would adopt BA in response to what competitors are doing."	Lutfi, Al-Khasawneh, et al. (2022); Chong & Lim (2022); Baig et al. (2021); Yadegaridehkordi et al. (2020)
COP2	"Many of our partners would expect our bank to adopt BA."	
COP3	"There is a trend in the banking sector to enhance the utilization of data analytics for business-related activities and decision-making."	
COP4	"BA is a necessity to compete with the other rivals."	
External Support		
ES1	"Vendors can provide the required training for BA adoption."	Maroufkhani et al. (2023); Chong & Lim (2022); Yadegaridehkordi et al. (2020)
ES2	"Vendors can provide adequate technical support for BA adoption."	
ES3	"Vendors who provide valuable assistance during the post-implementation stage encourage our bank to adopt BA."	
ES4	"Vendors actively market the use of BA."	
BA Adoption		
BA1	"Our bank uses BA to identify patterns and trends in our organizational data."	Chong & Lim (2022); Bany Mohammad et al. (2022)
BA2	"Our bank relies on BA to make well-informed decisions regarding the bank's strategy.	
BA3	"Our bank uses BA to monitor and evaluate the performance of the bank's operations."	
Bank Performance		
PER1	"I believe that using BA in our bank can result in a measurable improvement in financial performance."	Chatterjee et al. (2021); Yadegaridehkordi et al. (2020)
PER2	"I believe that using BA in our bank can result in a measurable improvement in operational performance."	
PER3	"I believe that using BA in our bank can increase employee productivity."	
PER4	"I believe that using BA in our bank can impact achieving better customer loyalty."	

* Reverse items

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