Migration Letters

Volume: 21, No: S13 (2024), pp. 164-184

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Adoption Of Big Data Analytics And Banks' Performance: The Moderating Role Of Analytics Capability

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Abstract

Big Data Analytics has revolutionized data-driven decision-making in the financial industry. This study investigates technological, organizational and environmental factors' influence on the utilization and implementation of big data analytics in the financial industry. We research the mediating role of adoption of big data analytics and its effect on bank performance in the context of Pakistani banks. The study fills the gap by taking into consideration analytics capability and bank strategy alignment as moderators between big data analytics adoption and the performance of the banks. The study uses a quantitative research approach. A structured questionnaire was used to collect primary data from managers of the public and private sector banks of Pakistan. SPSS software was used for statistical data analysis. Testing of hypothesis was performed using[1] regression analysis, and mediation and moderation results were determined through Model 14 of Preacher and Hayes PROCESS macro. The results reveal that all three factors namely technological, organizational, and environmental factors influence the adoption of big data analytics which in turn positively influences the banks' performance. Moreover, the adoption of big data analytics mediates the relationship between all three factors and bank performance. However, analytics capability and bank strategy alignment do not moderate the relation between big data analytics adoption and the performance of the banks. The study provides valuable insight for bank management regarding the benefits that big data analytics have to offer. This research also helps banking policy-makers better understand the need to align the banks' analytics capability and strategy, which are currently lacking in the banking system.The study is the first empirical study to investigate the moderating role of analytics capability and bank strategy alignment between the adoption of big data analytics and the performance of the banks, in Pakistan.

Keywords: *Big data, Bank performance, Big data analytics, TOE model, Organizational factors, Technological factors, Environmental factors, analytics capability-bank strategy alignment.*

1. Introduction

The era of digitalization has unleashed an unprecedented amount of data; the volume of data available today has surpassed anything previously imagined. The ever-expanding volume of data has given rise to the need to harness it, intending to uncover meaningful insights. The term Big Data (BD) is the technical name for the enormous amount of diverse data that is being

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generated and communicated quickly, and for which the traditional methods used to manage, analyze, retrieve, store, and display such enormous amounts of data are now inadequate and inefficient (Salih et al., 2021). Although, big data has gained massive recognition in the past decade origin of the term dates back to 1990 (Diebold, F. 2012). The massive influx of diversified data has led to the evolution of the conventional tools of data analytics. For the management and analysis of diversified and heterogeneous datasets the technology that is being utilized is referred to as "big data analytics". The application of BD analytics is across every sector. BDA has revolutionized the processes of various fields like healthcare, education, and insurance (Naveira et al., 2018).

The banking sector is predominantly data-driven, the raw data it carries contains the immense potential to enhance bank performance through improved decision-making. The adoption of big data analytics in the banking industry is becoming prevalent. By 2031, it is expected that the market for data analytics in banking will be worth USD 28.11 billion. In the banking sector, the usage of web-based applications has surged after COVID, which has led to a huge inflow of structured and unstructured diversified data. With the hike in the amount of data, it has become imperative for banks to adopt big data analytics timely. Here, BDA gears up to contribute significantly to the expansion of the financial sector. The banking industry can obtain a competitive advantage through numerous methods (Akter et al., 2016), which in turn increases bank performance. The adoption provides banks with tools and techniques to offer tailored and customized products to customers through the process of profiling and segmentation. It also facilitates banks' risk management system by uncovering suspicious behavior patterns timely.

The study aims to determine the influence of internal and external factors on the adoption of big data analytics (BDA) by banks in Pakistan, as well as the mediating role of BDA adoption and its impact on bank performance, and to know whether BDA adoption mediates the association of TOE factors and bank performance. There are very few studies that have explored the implications of big data analytics for banks. The study undertaken by Al-Dmour et al., (2020) suggested that similar studies as distinct developing countries have distinct resources, capacities, and systems. In parallel to it, to fulfill the gap in the existing literature this study aims to explore how the alignment in banks' analytics capability and business strategy moderates the association between BDA adoption and, performance of the banks. Using it as a moderator, we will be able to understand whether the alignment of a bank's analytics capability and strategy, strengthens or weakens the relations between big data analytics and the performance of the bank. The research questions of the study are: Which variables (technological, organizational, and environmental) positively influence commercial Pakistani banks' adoption of big data analytics? Is the performance of the bank influenced by the adoption of big data analytics? Is the relation between technological, organizational, and environmental factors and the performance of the bank mediated by big data analytics adoption? Is the relationship between the adoption of big data analytics and banks' performance moderated by analytics capability-bank strategy alignment (ACBSA)?

This is the prime time for conducting this study as the implementation of big data analytics by Pakistani banks is in the initiation stage, and it will help in comprehending the factors that led banks to this adoption. Along with this, the study will help in understanding the existence of a relationship between the adoption of BDA and banks' performance. Lastly, this study will be beneficial for banks' decision-makers as it will help them understand the importance of alignment between analytics capability, and bank strategy to enhance performance and to acquire competitive advantage. The paper is structured as follows: Section

2 presents the literature review, section 3 illustrates the methodology, section 4 presents the results and the final section presents the conclusion and recommendations.

2. Literature Review

The last decade has witnessed the rise of big data analytics, which has become a powerful analytical instrument. From being a buzzword to a mainstream technology it has been adopted by many organizations in the healthcare, education, and financial sector. Big data analytics BDA is significant as it uses information technology and quantitative analysis to improve organizational operations and decision-making (Aziz et al., 2023). Khanra et al., (2020) conducted a bibliometric synthesis of big data analytics literature of over ten years and discovered that health (Wang & Hajli 2017), retail (Akter & Wamba 2016), manufacturing (Dubey et al., 2016), supply chains (Chae, 2015) and education (Siemens, 2013) are many of the allied management areas where big data analytics significance is being investigated.

The effects of big data analytics (BDA) within the domain of the banking and financial sector have not been sufficiently studied (Aziz et al., 2023). Even though financial services have revolutionized as a result of technological advancements, particularly in the way that banks and FinTech businesses deliver their services (Hasan et al., 2020). The term "big data" in banking refers to the massive volume of data generated by banks, encompassing financial transactions of clients, credit records, payment records, website or app interactions, and customer service engagements. Big data analytics entails systematically analyzing this vast amount of client data to extract valuable insights that help in making wise decisions (Anonymous, 2023). There is a list of categories that can be used to group capabilities related to the tools used to generate superior insights: R, Python, Apache, IBM Cognos, and Google BigQuery are data mining tools; SAS visual analytics, Tableau, and Apache Spark are analytics tools, while Hadoop, Teradata, Pentaho, and Amazon RDS are storage tools (Maja & Letaba, 2022). Although there has been little research done in this area, big data applications in the banking industry are expanding quickly (Nobanee et al., 2022).

The theoretical foundation of this research rests on the resource-based view and technology-organization-environment TOE model. In the existing literature, these two frameworks are commonly employed to comprehend the drivers behind the adoption of innovative technology and its potential implications for firm performance (Lutfi et al., 2022). The BDA adoption is a tipping point for precise decision-making and ideal performance in the current industrial climate (Maroufkhani et al., 2020). The theories or models that are usually mentioned in the context of big BDA adoption are the Technological-Organizational-Environmental (TOE) framework (Tornatzky & Fleisher, 1990), Innovation Diffusion Theory (IDT, Rogers, 1962, 1995, and 2003), and the Technology Acceptance Model (TAM, Davis, 1989). However, the TOE framework is the most popular and frequently used way to conduct research on technology acceptance. The TOE model takes into account all internal and external variables that may have an impact on a firm's adoption of technology (Maroufkhani et al., 2020). Three context groups; technological, organizational, and environmental, are identified by the TOE model.

The RBV states that a company's primary resources determine its performance (Ghasemaghaei et al., 2017). Resources for a company could be both material and intangible assets, such as data, expertise, and operational practices. (Wade et al., 2004). The resource-based view (RBV) describes the relationship between a company's internal attributes (resources and capabilities) and its performance by considering the organization as an integration of capabilities and resources (Ciszewska-Mlinarič & Wasowska 2015). Galetsi et al. (2020)

conducted a study that applied the RBV theory to investigate the theoretical linkage between big data analytics utilization and organizational performance.

The focus of the technological environment lies on the attributes that could exert either positive or negative influences on the decision to implement a novel technology (Lai et al., 2018; Tornatzky & Fleischer, 1990). The study, contains three constructs; complexity, compatibility, and security and privacy. In big data analytics or system context, compatibility refers to how well-suited a company's existing security technology and management practices are to the big data systems' security requirements (Al-Dmour et al., 2020). "Technological complexity" refers to the level at which BDA technology is seen as intricate to use and understand within the organization, as outlined by Lai et al. (2018). In the banking industry, the ever-expanding data contain immense sensitive information, necessitating a prime focus on safeguarding it (Al-Dmour et al., 2020).

The research of (Merhi & Bregu, 2020; Phan & Tran, 2022) supports the idea that the readiness of IT infrastructure will positively influence the utilization of big data analytics. While findings from (Sumbal et al., 2019) study suggest that in developing countries, local and national companies might face budget constraints, making it challenging to afford the proper IT infrastructure and analysts required for optimal big data utilization. Employees' perception of BD analytics alignment with existing practices and its ease of use results in increased inclination toward acceptance and utilization of BDA (Maroufkhani et al., 2022).

Moreover, the utilization and integration of advanced technology is a complex undertaking, especially in developing countries like Pakistan. Banks within Pakistan are diligently working to establish a cohesive ecosystem to facilitate the seamless incorporation of BD analytics. As a result, we put forth the following hypotheses:

H_1 Perceived Technological factors positively impact the adoption of big data analytics (BDA) in commercial banks in Pakistan.

When discussing the adoption and implementation of an invention, the term "organizational factors" refers to the features of the company that either support or hinder these actions. (Gangwar, 2018). The study will focus on three specific factors: support from upper management, the orientation of business strategy, and the resources of the organization. Top management support is characterized by the degree to which the highest-level leadership provides assistance and dedication to the necessities of the system (Al-Dmour et al., 2020).

The finding of Al-Dmour et al., (2020), and Sumbal et al.(2019) studies are consistent with each other suggesting that in organizational factors the key factor is support from top management and organizational readiness. Organization-wide adoption and implementation are a result of active participation and commitment of top management through orienting organization strategy towards big data, taking data-based decisions and transforming organization culture (Park & Kim, 2021). The availability of financial resources within an organization positively affects the integration and execution of BDA. Firms with limited competencies and resources may face challenges in fully embracing Big Data Analytics (BDA) (Lutfi et al., 2022). Monetary commitment and support from management are essential for the adoption of big data analytics (Truong, 2022). As a result of the discussion mentioned previously, the following hypothesis is:

H_2 Perceived Organizational factors positively impact the adoption of big data analytics (BDA) in commercial banks in Pakistan.

Within the of TOE framework, the surroundings in which an organization operates are termed environmental factors (Gangwar, 2018). Given that analytics is a technical function that needs a supportive environment to be effective, some sectors are better suited to provide this environment than others. The decision of a firm to adopt a certain technology can be influenced by its competitor's actions (Shet et al., 2020). The active adoption of BDA by competitors will cause the fear of losing competitive edge in the organization and contrary to it if organizations in the industry are laid back in the adoption of BDA then the particular organization will also not have any giant leap in adoption (Lai et al., 2018). The government regulation can not only facilitate but at times hinder the adoption of BDA. The findings of (Al-Dmour et al., 2020) research indicated that industry composition and regulatory policies positively impact the level of practicing BD applications. The role of governments in providing access to public data, protecting intellectual property, and enforcing privacy and security regulations is crucial in influencing firms to adopt big data technologies and methodologies (Park & Kim, 2021). Consequently, we put forward the subsequent hypothesis:

H_3. Perceived Environmental factors positively impact the adoption of big data analytics (BDA) in commercial banks in Pakistan.

The findings of the Maroufkhani et al. (2020) study suggest that BDA adoption in SMEs mediates the effects of TOE factors on financial performance. The use of TOE factors as organizational innovation adoption predictors can improve firm performance by assisting in the identification of the critical components essential for effective execution (Maroufkhani et al. 2020). According to the study of Grant and Yeo (2018), TOE settings would influence how businesses performed and made decisions in the context of ICT. Additionally, a study conducted by Narwane et al. (2020) demonstrated empirically that innovation, like the cloud of things, might act as a mediator between its determinants and the performance of SMEs.

The existing literature has labeled the BDA adoption as a valuable resource to enhance bank performance (Al-Dmour et al., 2020). Belhadi et al. (2019) discussed that employing BDA leads to enhanced intra- and inter-organizational transparency and accountability, facilitates quicker and more accurate decision-making for managers, and improves employees' efficiency. The empirical analysis conducted by Lutfi et al., (2022) yields compelling evidence highlighting the significant influence of BDA acceptance on the performance of a firm. The results demonstrate that a broader implementation of BDA is linked to a more substantial positive influence on business performance. According to the observation of Maroufkhani et al. (2019), BD Analytics has been recognized as one of the primary capabilities that can enhance bank performance.

According to the literature even though the direct effect of TOE factors on firm performance suggests that certain factors within the organization's technology, organization, and environment can influence how well the firm performs. However, this influence is not just direct; it is also mediated by the adoption of a specific technology (BDA), which acts as an intermediary, channeling the impact of TOE factors on firm performance through its adoption and utilization. Thus, the proposed hypothesis is:

$H_{4.1}$ Big data analytics adoption mediates the relation between technological factors and the performance of the banks.

$H_{4.2}$ Big data analytics adoption mediates the relation between organizational factors and the performance of the banks.

$H_{4.3}$ Big data analytics adoption mediates the relation between environmental factors and the performance of the banks.

A company's capacity to use big data for the creation of business value is referred to as its big data analytics capability (BDAC) (Pathak et al., 2021). The resource-based view (RBV) is at the back end of BDA. According to the RBV, a corporation can be regarded as a set of assets and skills. The capacity of the firm to turn inputs into higher-value outputs is referred to as RBV theory (Amit & Schoemaker 1993). According to capabilities literature, firms' capabilities can be divided into two logically distinct but connected groups (Teece 2007). Operational capabilities enable an organization to operate and complete a specific task, and the second group of capabilities aids in the organization's growth and ability to generate revenue. These skills are referred to as dynamic skills (Teece 2007).

Strategic alignment in the setting of BDA refers to the value put on big data initiatives by the firm's top executives in attaining firm objectives. Rather than focusing solely on data management objectives, BDA strategic alignment focuses on the necessity of discovering company driving forces, fostering coherence between analytics and firm endeavors, defining objectives to incorporate analytics into business operations and strategies, and cultivating an atmosphere that promotes company achievement through data and analytics. (Pathak et al., 2021; Vassakis et al., 2021).

The term "BDAC-business alignment" was first used by Xie et al. (2022) to describe the seamless integration of analytics capacity with business objectives. The alignment between managers in charge of BD analytics and those supervising cross-functional domains encourages synergy within BD analytics, enabling smooth integration with functional operations to proficiently execute strategic initiatives (Xie et al., 2022). Businesses gain more empowerment when their company plan and BDA strategy are more aligned, to effectively address challenges in dynamic environments, leading to the creation of value-adding activities (Xie et al., 2022; Gölgeci et al., 2019). Considering the earlier discussion, the following hypothesis is suggested:

H_5 Analytics capability and bank strategy alignment moderate the relationship between the adoption of big data analytics and the bank's performance.

The processes of the banking sector have evolved with the advancement in technology in the form of BD Analytics, Artificial Intelligence, and Fintech. BDA is currently the most rapidly growing trend in the banking industry due to its considerable impact. (Nobanee et., al 2022). With the growing interest in using big data in the field of banking, this study intends to evaluate how the alignment of analytics capabilities with business strategy contributes to strengthening the link between BD analytics adoption and the performance of the bank. In developing countries like Pakistan where the adoption of any new technology is a slow and extensive process so this study will help in understanding the mechanism that banks adopt in Pakistan. Figure 1 shows proposed theoretical model.

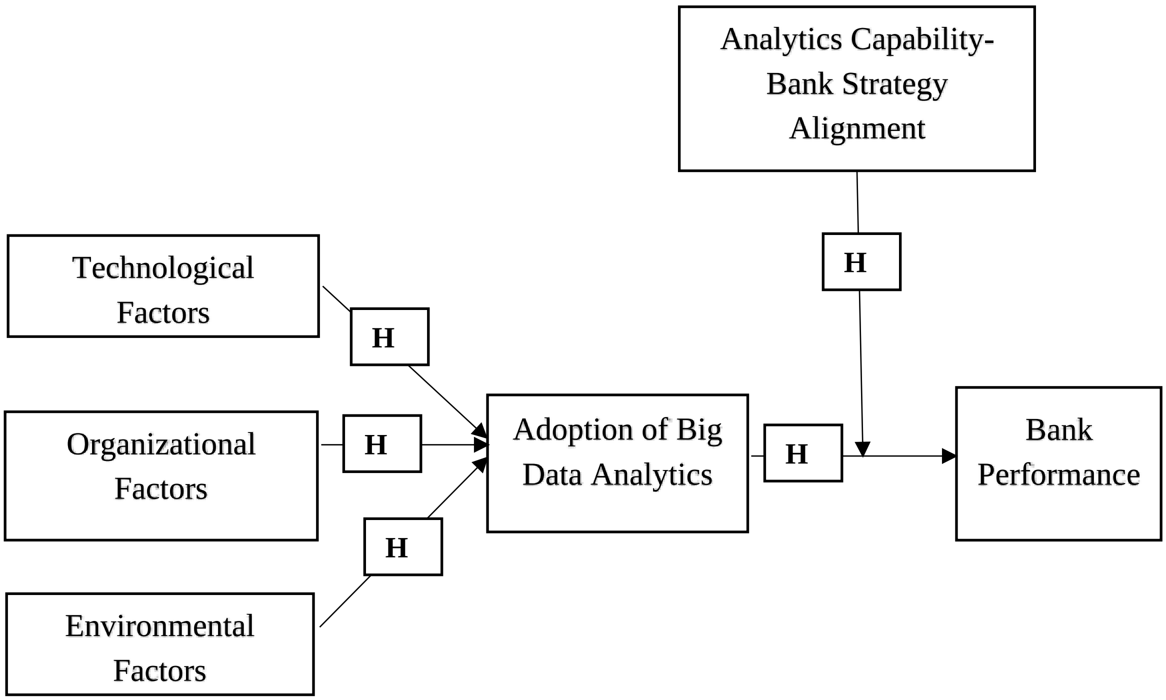

Figure 1. Theoretical framework of the study

3. Methodology

The hypotheses for this research are developed through a deductive approach. This study employs the quantitative research method to effectively attain the research objectives, and a cross-sectional study design. A purposive sampling technique is utilized in this study. Purposefully selecting participants can offer valuable perspectives relevant to the research question (Creswell 2014). The research's target population encompasses bank managers (top-level, middle-level, and frontline managers) in Pakistan, including both public and private sector banks. Bank managers are selected as the target population, as they are directly involved in the decision-making process and are well-informed regarding the current status of the bank in terms of big data analytics adoption. A questionnaire is utilized as the selected method for the collection of data in the current study. For conducting the research, only banks that specifically referenced big data analytics or data analytics are chosen for inclusion. The test were run on 157 sample size. The findings of Hair et al., (1998), suggest that a sample size of 100 participants is adequate for obtaining reliable results using SPSS in quantitative research. This study utilizes software (SPSS) for conducting statistical analysis, incorporating both descriptive and inferential analysis techniques. While mediation and moderation results are determined using Model 14 of Preacher and Hayes PROCESS macro. The questionnaire comprised close-ended questions. A seven-point Likert scale is utilized against five items except for the Adoption of Big Data Analytics (mediator), to allow participants to provide their responses, they can indicate their level of agreement using a scale ranging from "strongly disagree" (1) to "strongly agree" (7). Similarly, for the mediator, a 4-point Likert scale has been used to assess their level of practice, ranging from "not fully practiced" (1) to "fully practiced" (4). Table 2 presents the operationalization of the variables of the study.

Table 1 Measurement of Variables

	Constructs	Items	Sources
1	Technological Factors	9	Al-Dmour et al., (2020)
2	Organizational Factors	12	Al-Dmour et al., (2020)
3	Environmental Factors	7	Al-Dmour et al., (2020)
4	Adoption of Big Data Analytics	13	(Al-Dmour et al., 2020)
5	Bank Performance	6	Wu et al. (2015)
6	Analytics Capability–Business Strategy Alignment	17	Setia and Patel(2013)

4. Results and Analysis

The demographic statistics of the sample are presented in Table 3. The percentage of male respondents is 60.5% while that of female respondents is 39.5%. In the context of qualifications, 56.7% of respondents have done Masters, 38.9% have done Bachelors, 3.2% have done M.Phil, and just 1.2% held a Ph.D. degree. The percentage of private banks in the sample is 91.3% while that of public banks is 8.7%. Additionally, 59.9% of the respondents belong to the front-line management level, 31.2% belong to the middle-level management and 8.9% belong to top-level management. Lastly, the percentage of respondents who did not receive any big data analytics training is 74.5% while those of who have received training is 25.5%.

Table 3 Demographic Statistics

Category		Frequency	%
Gender	Male	95	60.5
	Female	62	39.5
Qualifications	Bachelors	61	38.9
	Masters	89	56.7
	M.Phil.	5	3.2
	PhD	2	1.2
Bank Type	Private	21	91.3
	Public	2	8.7
Managerial Level	Top-Level Management	14	8.9
	Middle-Level Management	49	31.2
	Front-Line Management	94	59.9
Received any training of Big Data Analytics	No	117	74.5
	Yes	40	25.5

The reliability analysis results, as presented in Table 4, reveal that the "Cronbach's alpha" value of all the variables is more than the cut-off point of 0.7 (DeVellis 2012). This finding indicates that the scale as a whole has good internal consistency, demonstrating that all the items in each variable are measuring underlying constructs consistently. Hence, the instrument is reliable for further examination and analysis.

Table 4 Reliability Analysis

Variables	No. of Items	Cronbach's alpha
Technological Factors	9	.821
Organizational Factors	12	.887
Environmental Factors	7	.744
Adoption of Big Data Analytics	13	.886
Analytics Capability–Business Strategy Alignment	17	.903
Bank Performance	6	.871

Table 5 indicates the descriptive statistics of the variables. The values of skewness (-.723 to -1.206) are between the range of -1 and +1 while values of kurtosis (0.025 to 1.347) are within the range of -3 and +3 which suggests that the data is normally distributed. (Brown, 2006).

Table 5 Descriptive Statistics

	Mean	Std.	Skewness	Kurtosis
Technological Factors	5.7962	.57168	-.712	1.347
Organizational Factors	5.8232	.60154	-.716	1.150
Environmental Factors	5.6843	.56453	-.210	.605
Adoption of Big Data Analytics	3.5595	.38801	-1.206	1.222
Analytics Capability–Business Strategy Alignment	5.9314	.55329	-.577	.025
Bank Performance	5.8344	.67923	-.205	.159

The result of the correlation analysis is presented in Table 6. The result show that there is a positive correlation between all the variables.

Table 6 Correlations

	1	2	3	4
Technological Factors	1			
Organizational Factors	.592**	1		
Environmental Factors	.716**	.628**	1	

Bank Performance	.536**	.630**	.578**	1

**. Correlation is significant at the 0.01 level (2-tailed).
TF: Technological Factors, OF: Organizational Factors, EF: Environmental Factors, BP: Bank Performance

Regression Analysis

The result in Table 7 indicate that the value of tolerance of all the variables is less than 1 while the value of VIF of all the variables is less than 10 (Hair et al., 2010) which indicates that the issue of multi-collinearity does not exist. Furthermore, the value of standardized beta shows the contribution of independent variables to the model. The t- value for the technological factor ($t = 1.476$, $p > .05$) shows that the regression is insignificant. While the t-value for organizational factors ($t = 5.186$, $p < .05$) shows that the regression is significant. Similarly, the t-value for environmental factors ($t = 2.479$, $p < .05$) shows that the regression is significant.

Table 7 Coefficients and Collinearity Statistics

				Collinearity Statistics	
Model	**β**	**t**	**Sig.**	**Tolerance**	**VIF**
(Constant)		1.488	.139		
TF	.130	1.476	.142	.453	2.206
OF	.410	5.186	.000	.565	1.771
EF	.227	2.479	.014	.423	2.365

Dependent Variable: BP
TF: Technological Factors, OF: Organizational Factors, EF: Environmental Factors, BP: Bank Performance

The model summary in the Table 8 provides an overview of the regression model's goodness-of-fit and overall performance. The adjusted R square value shows that the predictor variables (technological factors, organizational factors, and environmental factors) can account for a change of 44.9% in the dependent variable (performance of the Bank).

Table 8 Model Summary

					Change Statistics				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**
1	.678[a]	.459	.449	.50439	.459	43.300	3	153	.000

a. Predictors: (Constant), TF, OF, EF
b. Dependent Variable: BP
TF: Technological Factors, OF: Organizational Factors, EF: Environmental Factors, BP: Bank Performance

The ANOVA test is presented in Table 9. The regression analysis determines the effect of independent factors on the dependent variable. The level of significance is less than 0.05, indicating that the model is suitable to account for the variance introduced by predictors into the dependent variable i.e. $F(3,153) = 43.300$, $p < 0.05$.

Table 9 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.047	3	11.016	43.300	.000[b]
	Residual	38.925	153	.254		
	Total	71.972	156			

a. Dependent Variable: BP
b. Predictors: (Constant), TF, OF, EF
TF: Technological Factors, OF: Organizational Factors, EF: Environmental Factors, BP: Bank Performance

Mediation and Moderation Results

Table 10 presents the result of the moderation analysis. The effect of the extent of adoption of BD analytics on the performance of the bank is significant with a beta value of .5439 which highlights that a one percent change in the level of adoption of big data analytics causes a 54.39% change in bank performance. The result shows that the influence of analytics capability and bank strategy alignment on bank performance is significant with a beta coefficient value of .3378 which indicates that the 1 percent change in analytics capability and bank strategy alignment causes a 33.78% in bank performance.

Additionally, the interaction term in Table 10 shows the result of the moderating effect of analytics capability and bank strategy alignment on the relation of the adoption of BD analytics and the performance of the bank. The interaction term signifies that the moderating effect of analytics capability and bank strategy alignment is insignificant with a significance level of .4169. Furthermore, the presence of zero between the upper and lower boundaries in the interaction indicates that moderation is insignificant. These findings are in contrary to those of previous research which suggests that the absence of alignment, which reflects a mismatch between the organization's current decision-making mindset and the potential usefulness of Big Data Analytics (BDA) capabilities, can negatively impact an organization's performance. (Akter et al., 2016). The finding of (Xie et al., 2022) highlights that BDAC-bank strategy alignment involves seamlessly integrating analytics capabilities into business activities. The present study findings indicate that there is a gap between the bank's BDA implementation plan, and the bank's strategic goals and objectives. Thus, the findings do not conform to the existing literature.

Table 10 Moderation Effects of Analytics Capability–Bank Strategy Alignment

Outcome Variable: BP

Model	coeff	Se	t	p	LLCI	ULCI

Constant	4.3445	.6488	6.6965	.0000	3.0627	5.6262
A	.5439	.1278	4.2568	.0000	.2915	.7964
ACBSA	.3378	.1256	2.6895	.0080	.0897	.5860
Int_1	.1446	.1776	.8141	.4169	-.2064	.4956

A: Adoption of Big Data Analytics, ACBSA: Analytics Capability-Bank Strategy Alignment

The result in the table 11 shows that the effect of the technological factors on the performance of the bank is significant with a beta value of .2544. The influence of the usage of big data analytics on bank performance is significant with a beta value of .5439 which highlights that a one percent change in the adoption of big data analytics causes a 54.39% change in the performance of the bank. The finding are consistent with the study of Maroufkhani et al. (2019) in which BDA had been acknowledged as one of the key capabilities that can enhance bank performance.

Mediation Effects of the Extent of Adoption of Big Data Analytics

Table 11 Outcome Variable: BP

Model	**Coeff**	**Se**	**t**	**p**	**LLCI**	**ULCI**
constant	4.3445	.6488	6.6965	.0000	3.0627	5.6262
TF	.2544	.1120	2.2707	.0246	.0330	.4757
A	.5439	.1278	4.2568	.0000	.2915	.7964

TF: Technological Factors, A: Adoption of Big Data Analytics

The table below shows the significant positive effect of technological factors on the adoption of big data analytics, and a one percent change in technological factors will cause a 27.76 percent change in the adoption of big data. The findings of current study are consistent with the previous studies which observed the impact of these factors on the implementation of advanced technology in various industries. The study of Al-Dmour et al., (2020) also highlights similar findings, in the banking industry.

Table 12 Outcome Variable: A

Model	**Coeff**	**Se**	**T**	**p**	**LLCI**	**ULCI**
Constant	-1.6090	.2897	-5.5532	.0000	-2.1813	-1.0366
TF	.2776	.0497	5.5800	.0000	.1793	.3759

TF: Technological Factors

The result of the mediation effect is presented in the table 11 and 12. The result indicates that the effect of technological factors on bank performance through the adoption of big data analytics is insignificant. Due to the insignificant effect of technological factors on the performance of the bank (direct effect) and the impact of a technological factor on bank performance through the big data analytics adoption (indirect effect) is significant thus full mediation is taking place. The finding are in line with the study of the Maroufkhani et al. (2020) which suggested that BDA adoption in SMEs mediates the effects of TOE factors on financial performance. Figure 2 shows the moderation plot (A) for the effect of the moderator (ACBSA) on the relation of the adoption of big data analytics and the performance of the bank. The parallel lines in figure 2 show that there is no interaction and analytics capability and bank strategy alignment does not moderate the relationship.

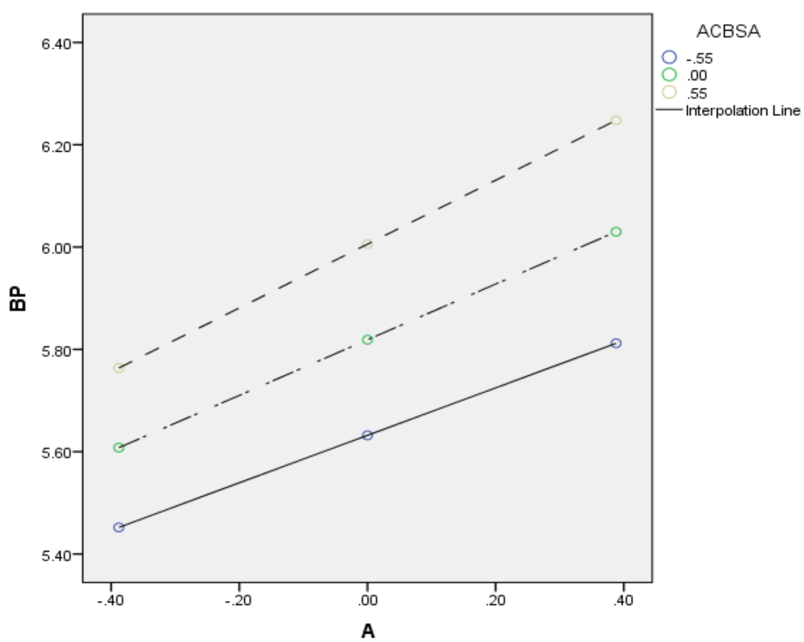

Figure 2 Moderation Plot(A)

Table 13 displays the findings of the moderation analysis. The beta coefficient value of .3734 means that a 1% change in the extent of big data analytics adoption results in a 37.34% change in bank performance. The influence of the analytics capacity and bank strategy alignment on the performance of the bank is also positive and significant, as shown by the beta value of .2736, which shows that a 1% change in the analytics capacity and bank strategy alignment results in a 27.36% change in performance of the bank.

The interaction term in the table 13 also illustrates the outcome of the moderating effect of analytics capacity and bank strategy alignment on the relation of BDA adoption and the performance of banks. The moderating role is insignificant with a significance level of .6974, as indicated by the interaction term. Additionally, the existence of zero between the upper and lower bounds of interaction shows that moderation is insignificant.

Table 13 Moderation Effects of Analytics Capability– Bank Strategy Alignment

Outcome Variable: BP

Model	**coeff**	**Se**	**t**	**P**	**LLCI**	**ULCI**
Constant	3.4434	.5824	5.9121	.0000	2.2927	4.5941
A	.3734	.1318	2.8338	.0052	.1131	.6337
ACBSA	.2736	.1084	2.5240	.0126	.0594	.4878
Int_1	.0674	.1730	.3896	.6974	-.2744	.4092

A: Adoption of Big Data Analytics, ACBSA: Analytics Capability-Bank Strategy Alignment

Table 14 shows that the effect of the organizational factors on the performance of the bank is significant with a beta value of .4094. The effect of big data analytics adoption on the performance bank is significant with a beta value of .3734 which highlights that a one percent change in the adoption of big data analytics causes a 37.34% change in the performance of the bank. The studies of Maroufkhani et al., (2020), Dubey et al., (2020), and Rajabion et al., (2019), concludes the same result regarding the effect of BDA adoption on firm performance however in the context of different industries.

Table 14 Mediation Effects of the Extent of Adoption of Big Data Analytics

Outcome Variable: BP

Model	**Coeff**	**Se**	**t**	**p**	**LLCI**	**ULCI**
constant	3.4434	.5824	5.9121	.0000	2.2927	4.5941
OF	.4094	.1003	4.0819	.0001	.2112	.6075
A	.3734	.1318	2.8338	.0052	.1131	.6337

OF: Organizational Factors, A: Adoption of Big Data Analytics

The table below shows that the organizational factors have a positive influence on the adoption of BDA, and a one percent change in organizational factors will cause a 35.74 percent change in BD adoption. The research findings imply that organizational characteristics have a favorable effect on the utilization of BD analytics. These findings are similar to the research of (Lutfi et al., 2022) which proposes that in organizational factors, support from upper management, and organizational preparedness are primary factors. The studies of Lutfi et al., (2022), and Truong, (2022) emphasized on the importance of monetary commitment and support from management to facilitate its adoption. Thus, the findings are in accordance with the previous conducted in a similar context.

Table 15 Outcome Variable: A

Model	**Coeff**	**Se**	**t**	**p**	**LLCI**	**ULCI**
Constant	-2.0812	.2525	-8.2427	.0000	-2.5799	-1.5824
OF	.3574	.0431	8.2862	.0000	.2722	.4426

OF: Organizational Factors

Table 14 and 15 displays the outcome of the mediation effect. According to the finding, the effect of organizational factors on bank performance through the adoption of BDA is significant. The indirect effect, like the direct effect, is significant since there is no zero between the lower and upper bound levels. Partial meditation is occurring because the effect of organizational factors on the performance of the bank (direct effect) and the effect of organizational factors on the performance of the bank through the degree of big data analytics adoption (indirect effect) are both significant. The findings are consistent with the findings of Maroufkhani et al. (2019).

Figure 3 shows the moderation plot (B) for the effect of the moderator (ACBSA) on the relation between big data analytics adoption and the performance of the bank. The parallel lines in figure 3 show that there is no interaction and analytics capability and business strategy alignment do not moderate the relationship.

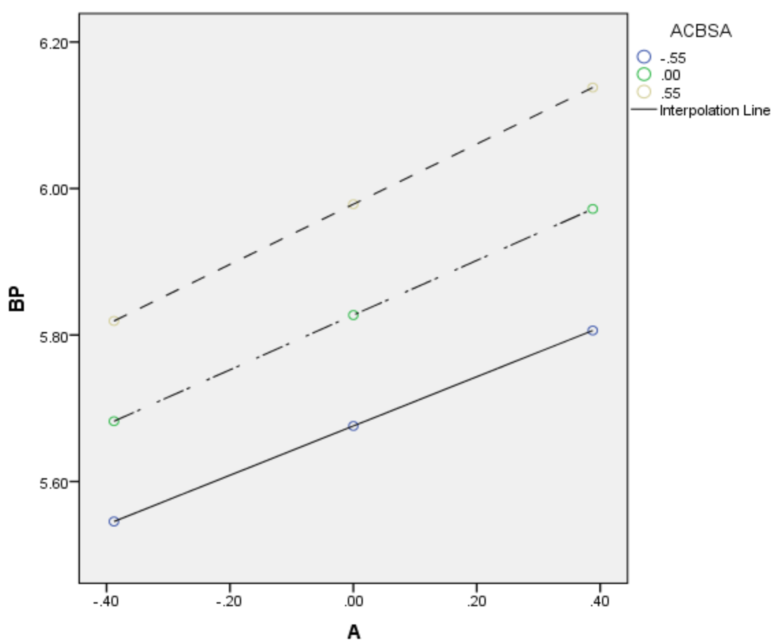

Figure 3 Moderation Plot (B)

The moderation analysis results are shown in Table 16. The impact of the adoption of BDA on the performance of the bank is positive and significant with a beta value of .4422 which highlights that a one percent change in the adoption of big data analytics causes a 44.22 percent change in bank performance. Likewise, the result shows that the effect of analytics capability and bank strategy alignment on bank performance is positive and significant with a beta coefficient value of .3309 which indicates that the 1 percent change in analytics capability and bank strategy alignment causes a 33.09 percent change in bank performance.

Additionally, the interaction term in the table 16 represents the moderating effect results of analytics capability and bank strategy alignment on the relation of adoption of big data analytics and performance of the bank. The interaction term signifies that the moderating effect is insignificant with a significance level of .7200. Furthermore, the presence of zero between the upper and lower boundaries in the interaction indicates that moderation is insignificant.

Table 16 Moderation Effects of Analytics Capability– Bank Strategy Alignment

Outcome Variable: BP

Model	Coeff	Se	t	P	LLCI	ULCI
Constant	3.7930	.5450	6.9603	.0000	2.7164	4.8697
A	.4422	.1284	3.4424	.0007	.1884	.6959
ACBSA	.3309	.1039	3.1863	.0017	.1257	.5361
Int_1	.0629	.1752	.3592	.7200	-.2832	.4091

A: Adoption of Big Data Analytics, ACBSA: Analytics Capability-Bank Strategy Alignment

The result in Table 17 shows that the impact of environmental factors on bank performance is positive and significant with a beta coefficient value of .3579 which indicates that the 1 percent change in environmental factors causes a 35.79 percent change in the performance of the bank. The direct effect of environmental factors on bank performance is significant. The effect of BD analytics adoption on the performance of the bank is significant with a beta value of .4422. In recent years, various studies have been undertaken to investigate the effect of BDA on a firm's performance. In light of (Phan & Tran, 2022) findings, the utilization of Big Data Analytics (BDA) in banks yields dual benefits for enhancing banking performance. Firstly, it directly enhances market and operational performance by providing valuable insights and enabling efficient processes. Secondly, BDA improves risk management performance, resulting in an overall elevation of the bank's performance. Thus, the finding of the present study suggests that the adoption of BDA improves the performance of banks, which is similar to those of previous studies.

Mediation Effects of the Extent of Adoption of Big Data Analytics

Table 17 Outcome Variable: BP

Model	Coeff	Se	t	p	LLCI	ULCI
constant	3.7930	.5450	6.9603	.0000	2.7164	4.8697

EF	.3579	.0962	3.7209	.0003	.1679	.5480
A	.4422	.1284	3.4424	.0007	.1884	.6959

EF: Environmental Factors, A: Adoption of Big Data Analytics

The result in the table below indicates that environmental factors have a positive and significant effect on the adoption of BDA, and a one percent change in environmental factors will cause a 31.79 percent change in the degree of adoption of big data. The findings of the study show that the environmental factor is another factor that encourages the adoption of big data adoption in banks. These findings are in accordance with the findings of the (Gangwar, 2018) and Sumbal et al. (2019) study which highlights that the relationship is significant as it directly impacts the firm's decision-making.

Table 18 Outcome Variable: A

Model	**Coeff**	**Se**	**t**	**p**	**LLCI**	**ULCI**
Constant	-1.8068	.2796	-6.4621	.0000	-2.3591	-1.2545
EF	.3179	.0489	6.4937	.0000	.2212	.4146

EF: Environmental Factors

Table 17 and 18 displays the outcome of the mediation effect. The findings from Table 18 indicate that there is a significant effect of environmental factors on bank performance through the degree of big data analytics adoption. The indirect effect, like the direct effect, is significant since there is no zero between the lower and upper bound levels. Partial meditation is occurring because the direct effect and indirect effect are both significant. The finding are in line with study of Maroufkhani et al. (2019).

Figure 4 shows the effect of the moderator (ACBSA) on the relation of big data analytics adoption and the performance of the bank. The parallel lines in figure 4 show that there is no interaction and analytics capability and business strategy alignment do not moderate the relationship.

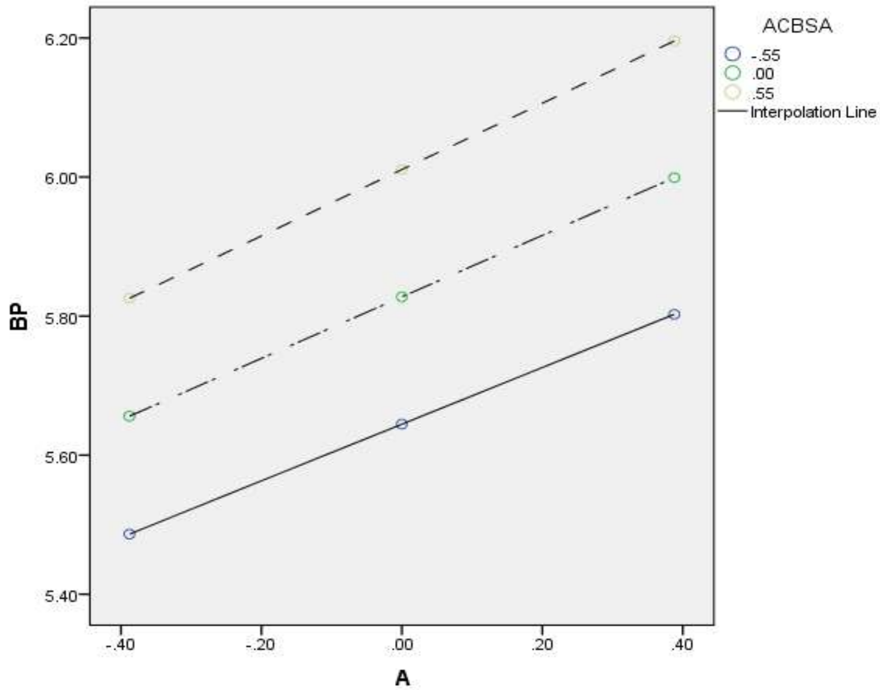

Figure 4 Moderation Plot (C)

5. Conclusion and Recommendations/Implications of the Study

The purpose of this research is to investigate the variables which affect the acceptance of BD analytics by Pakistani banks as well as the mediating role of BDA adoption along with the effects of that adoption on the performance of banks. Additionally, the moderating role of BDA capabilities and bank strategy alignment. The outcomes of the research highlight that the three TOE factors have positive impact on the adoption of BD analytics. The adoption of BD analytics mediates the relation between perceived factors and the performance of the banks. All three variables considerably affect the acceptance of BDA which in turn influences bank performance. However, the findings reveal that the alignment between BDA capabilities and bank strategy do not moderate the relation between the big data analytics use and the performance of the banks.

Following implication are drawn from the study:

- In terms of technological factors, the bank management has to ensure capacity development in terms of compatible and secure IT systems. Along with it, to ease the complexity that might be faced by employees, management should work to arrange workshops and training sessions.
- Additionally, in terms of organizational factors top management can work to create synergy between strategy orientation and the bank’s resources (financial, IT, and human resources). To optimize the usage of BDA, banks have to improve their internal controls.
- While, in the case of environmental factors, it is more about external influence. The management should be able to timely adapt to the changing competition structure and government policy.

- The research has provided further insightful information regarding the implications of BDA on the performance of banks. BDA can contribute an essential part in enhancing a bank's efficiency through, customer segmentation, and personalization, process optimization, regulatory compliance, and risk management.
- The study also offers an awareness to the top management of the banks that is responsible for the strategy formulation, regarding the lack of alignment between analytics capability and bank strategy. It is evident from the finding, regardless of the interest that top management has in big data, it is just considered a tool that is used to perform some basic task rather than a process that can be used organization-wide optimize the bank operations. The possession of capabilities alone is not enough, banks have to align BDA strategy with the bank's goals and objectives to fully utilize the potential of BDA.

The future studies can be conducted with a large sample size. In this study, the "TOE model" is used as a theoretical base, however for future studies "Technology Acceptance Model" can be used as theoretical base. It can be used to study the intent behind BDA implementation which is influenced by their perceptions. In the future, the study can be conducted to examine post-adoption results, the Expectation Confirmation Theory (ECT) can be used as a theoretical base to understand how banks' expectations, satisfaction, and continued usage behavior are influenced after the adoption of BDA systems or tools. Additionally, future study can be conducted on similar patterns in developed countries where the strategy formulation process might be different, thus comparative study can provide some valuable insights.

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