ORGANIZATIONAL READINESS FOR BIG DATA ANALYTICS, BUSINESS ANALYTICS ADOPTION AND DATA-DRIVEN CULTURE: THE CASE OF TURKISH BANKING SECTOR

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Abstract
This paper purposes to determine the mediating role of business analytics on the relationship between barriers on big data and data-driven culture in developing economies. The sample of this paper is 193 individuals working at eight commercial banks in two provinces of Turkey. The dataset is gathered using Partial Least Squares Structural Equation Modeling (PLS-SEM). The empirical findings indicated that barriers of big data for organizational preparation have been found to have a statistically significant negative effect on adoption of business analytics and data-driven culture. Adoption of business analytics is found to have a full mediation impact on the relationship between barriers of big data and data-driven culture. Bank employees put forward lack of qualified sources as the most important big data barrier among barriers of big data. The results highlight the importance of required resources for organizational preparation and qualified personnel.

Keywords: big data analytics and barriers, business analytics adoption, data-driven culture, organizational readiness, banking

1. INTRODUCTION

Big data and business analytics have gained increasing interest among scientists and practitioners to answer questions about how ubiquitous data can create new value, how that value is made, and how that value is shared among parties and contributors to the data (Vidgen et al., 2017). Over the last decade, the volume, velocity, and variety of data has expanded the topic of big data, business analytics, and data-driven culture. The current era, which is referred to as big data revolution, necessitates an era of digital change, accelerating globalization and continuous progress toward a digital world economy (Schmitt, 2023). Data, which is the most important force for this progress, is recognized as the engine of the global digital economy. Organizations have changed their business strategies to build a data-driven culture that generates value from data to utilize the power of data and analytics (Samarasinghe and Lokuge, 2022). Because big data and business analytics have the potential to fundamentally change the way companies do business. In a survey conducted by New Vantage Partners, which explored this shift in detail, only one-third of respondents reported that they have created a data-driven culture, while almost all respondents indicated that they want to move in this direction (Davenport and Bean, 2018). Big data analytics enables measurements and analytics in a way that completely redefines the management skills, function, and scope of businesses (Carillo et. al., 2019). Building a data-driven culture is crucial to keep up or survive in a data-centric world. As a result of the rapidly increasing amount of data being generated from the internal and external environment of businesses, it is crucial for the survival of the organization that organizations are ready for big data analytics and adopt it in business *analytics*.

Organizations have made a conscious effort to shift from intuition-based decision-making to evidence-based decision-making. Due to the availability of data and supporting information technology infrastructure, such a

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paradigm shift is happening faster than many realize (Delen and Ram, 2018). Upon this shift, the Turkish banking system started to use digital applications through Internet banking in the late 1990s and early 2000s and 3G technology since 2000. Digital transformation has accelerated in the Turkish banking sector since 2015 and continues with WAP (Wireless Application Protocol) banking services (Yıldırım, 2020). As in other countries, the Turkish banking sector faces new obstacles in a rapidly transforming business environment. Banks have adopted and implemented various technologies, tools, and tactics that enable organizations to collect, analyze, and use data to improve decision-making processes and operational efficiency to overcome these obstacles and stay ahead of the competition. Therefore, the adoption and use of business analytics in the local banking sector is critical. (Karaçoban, et al., 2023). In the era of digital innovation, big data has particularly impacted various sectors, especially the banking sector. Banks are currently facing the challenge of managing large amounts of financial and customer data. These challenges include banking areas such as branch performance, sales, risk assessment, electronic banking, and customer requests and needs. The adoption of big data analytics has emerged as an indispensable administrative tool that facilitates the analysis of the dynamic business environment and promotes decision-making to meet this challenge (Bany Mohammed et al., 2022; Horani et al., 2023). According to Hung (2020), big data analytics are very useful in improving the marketing and risk management performance of commercial banks. Within this context, data analytics can contribute to solving and improving banking problems and achieving the best outcomes for decision-making. In the present literature, research on the barriers to big data analytics applications in the context of developing countries such as Turkey and studies on business analytics and data-driven culture are very limited. Therefore, the research questions that form the basis of this study are as follows:

Research Question 1: What are the barriers to big data analytics implementation for employees in the Turkish banking sector?

Research Question 2: What are the effects of business analytics adoption on data-driven culture in Turkish banking sector?

These questions are addressed from the resource-based view framework, which includes organizational factors including readiness for big data analytics, business analytics adoption, and a culture of data-driven, including legal, financial, relational, informational, and organizational resources (Barney, 1991). Organizations will be successful if they can evoke the potential of resources. The resource-based view is the idea that an organization can develop capabilities to use resources appropriately. Therefore, the available data must be analyzed effectively (Delen & Zolbanin, 2018). With this understanding, we first examined the existing literature on organizational barriers to big data analytics, business analytics adoption, data-driven culture, and related concepts. Then, a research model was developed to examine these variables. Primary data collected from 8 commercial banks in Turkey (Ardahan, Kars) were analyzed using PLS-SEM. By examining the impact of barriers to big data analytics on data-driven culture and the mediating role of business analytics adoption in this impact through a holistic model, this research provides valuable insights for both researchers and practitioners. The study first presents the literature on organizational readiness for barriers to big data analytics, business analytics adoption, and data-driven culture. Then the formulated research model and hypotheses are presented. The applied research methodology is discussed and then the data analysis process is detailed. The paper concludes with a discussion including conclusions, implications, limitations, and suggestions for future research.

2. BUSINESS ANALYTICS ADOPTION

In the era of big trends, digital transformation, and technological advancements are either driven or powered by data. Although data is ubiquitous, what makes data a valuable asset is the useful and hidden information hidden within it. Finding this information and making it useful is the core subject of analytics (Duan & Xiong, 2015; Bayraktar et al., 2024). In general, analytics is the ability to discover meaningful patterns, unique knowledge, and information in data. In this sense, business analytics is a specialized application or subset of analytics that uses tools, techniques, and principles to develop solutions to very complex business problems (Delen and Ram, 2018). The continued digitization of all aspects of commercial activities leads to the generation

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of large amounts of data, resulting in an increasing focus on analytics as the primary tool for extracting value from data (Menukin et al., 2023).

Business analytics, which is responsible for transforming raw data into business insights, is seen as one of the best ways to stay balanced in digital turmoil by using information technology, statistical analysis, quantitative methods, and mathematical and computer-based models (Appelbaum et al., 2017; Almazmomi, Ilmudeen & Qaffas, 2022). In other words, it can be considered as a set of techniques, technologies, systems, methods, and applications that analyze critical business data that help a business better understand its internal and external environment and make timely business decisions (Nam, Lee, and Lee, 2019). Business analytics is substantially about extracting value from data. Extracting value from data requires aligning desired behaviors with organizational culture, along with analytical tasks and capabilities (Acito & Khatri, 2014). Due to the volume, variety, and velocity at which data is generated, business analytics requires extensive computation, and the tools, techniques, and algorithms in these computations need to be adopted by employees (Delen & Ram, 2018). In other words, business analytics adoption is the skill to accurately process and analyze the data collected by the dynamic capabilities of the business.

3. ORGANIZATIONAL READINESS FOR BIG DATA ANALYTICS

This study is designed to identify organizational readiness for the banking sector based on employee perceptions of the factors hindering the adoption of big data analytics. Organizational readiness is the degree to which firms can manage, support, or react to changes in the business environment. A sense of readiness for business changes has a positive impact on innovative activities (Binsaeed, 2023). Organizational readiness is all about learning and adaptation through the coordination of people, processes, systems, and performance measurement. An organization allocating resources, building information technology infrastructure, and hiring employees with the necessary business analytics skills are all indicators of organizational readiness (Hung et al., 2021). However, organizational readiness is conceptualized with psychological factors such as commitment to change as well as structural components such as change capacity and contextual factors, and there is no consensus on the relevant factors. Organizational readiness models require a context-specific assessment and should be tailored to the relevant field (Jöhnk et al. 2021).

Big data analytics emerged from two sources, “Big Data” and “Data Analytics”. Big data is the storage and analysis of complex, voluminous data using a range of technologies. Data analytics refers to the science of examining raw data to extract useful information using analytical tools such as mining/predictive analytics and descriptive analytics (Raut et al., 2021).

While organizations are investing in using big data, the true realization of the benefits of big data depends on organizations being fully prepared to embrace big data. Nasrollahi and Ramezani (2020) identified 50 criteria to assess organizational readiness for big data adoption. Implementation of these criteria brings about a cultural revolution in the organization. Managerial and cultural barriers need to be overcome to benefit from data and analytics (New Vantage Partners, 2020).

Organizational readiness relates to new changes in the corporate atmosphere that will replace old-style processes. The orchestration of big data is key to determining organizational readiness; the culture of the firm plays a very dynamic role in using big data analytics and management capabilities to predict the readiness factor of the company (Binsaeed, 2023). While numerous factors influence big data analytics readiness (Kalema and Mokgadi, 2017), it is widely acknowledged that there are a few common themes regardless of industry, and these are organizational structure, IT infrastructure, open communication, optimized business processes, measurement of key performance indicators, and a culture of trust (Hizam-Hanafiah et al., 2020; Antony, et al., 2023). An integral part of organizational readiness is technology readiness. The development of facilitating technologies such as the Internet of Things (IoT), cloud computing, autonomous robots, cyber-physical systems, augmented reality, and artificial intelligence has made technological readiness multidimensional (Frank et al., 2019). Technological readiness refers to the extent to which individuals in a firm perceive the benefits and actual uses of digital transformation. Fostering this digital readiness, where individuals in a firm are willing and able to use such technologies, is the key to a successful digital transformation (Nurfadilah et al., 2022).

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4. DATA-DRIVEN CULTURE

Organizational culture is a very complex concept to understand and define. Researchers have made various definitions of organizational culture, but they have not reached a consensus on a single definition (Halis & Naktiyok, 2003; Gül & Aykanat, 2012). Some argue that organizational culture encompasses almost all areas of an organization, while others call it the glue that holds an organization together (Gupta & George, 2016). As a general definition, organizational culture constitutes a set of shared mental assumptions that lead to interpretation and action in organizations by defining appropriate behavior for various contexts. Accordingly, subjects such as an organization's values, activities, philosophy, ideals, beliefs, norms, etc. are considered within the organizational culture (Rahman & Hadi, 2019; González-Torres, 2023). A data-driven organizational culture, on the other hand, is about all functions of the organization and management levels' finding, using, and transforming data into decisions (Kugler, 2022). In other words, data-driven culture can be understood as a special form of organizational culture (Kremser & Brunauer, 2019). Data-driven culture can also be referred to as a “decision-making culture” involving managers and employees at all hierarchical levels. (Gupta and George, 2016; Vidgen et al., 2017). Businesses need to have an appropriate culture to derive value from their work and to benefit from business analytics solutions at a high level (Chaudhuri et al., 2024).

The appropriate culture in the digital age is considered to be a data-driven culture. This is because data-driven culture is a specific cultural field that enhances learning, communication, and knowledge sharing, and successfully transforms and implements new ideas and processes. For this reason, many studies attribute the failures of big data projects to the lack of a supportive organizational culture rather than a lack of technological infrastructure (Karaboğa et al., 2023). While the existing literature emphasizes the importance of a data-driven culture to leverage data and analytics (Davenport and Bean, 2018), the scarcity of information on the specific characteristics of organizational culture makes it difficult to change an organization's culture to one that emphasizes data and analytics (Kugler, 2022). According to the “data and AI executive survey” conducted by New Vantage Partners (2022), most firms (91.9%) strongly agree that the biggest challenges to becoming data-driven organizations are cultural. Cultural barriers come in a variety of forms, from evolving business processes to outdated organizational structures and natural human resistance to change. The digital revolution impacts organizational cultures by reshaping social interactions and cultural elements while introducing technologies as a tool to manage changing norms, behaviors, and beliefs. With the abundance of data and the growing importance of data-driven decision-making in digital business strategies, the concept of data-driven culture has gained importance, especially in promoting the adoption of technologies such as big data analytics and artificial intelligence (Anton et al., 2023). As data-driven decisions have been made in business processes, it is important for companies to adopt a data-driven culture to survive in the digital world. In today's world, it is important for organizations to be data-driven and have this foundation to take advantage of the technology at our fingertips.

5. HYPOTHESES

Data culture has emerged as a topic of discussion in the context of big data and big data analytics (Kremser & Brunauer, 2019). Especially in a rapidly changing business environment, organizations need to be data-driven to stay one step ahead of the competition. However, simply accessing data is not enough. Success in a data-driven organization requires not only the right technology and data infrastructure but also a culture that is ready and willing to use data to make informed decisions. This is the exact point where organizational readiness comes into play (Jochberger, 2023). Readiness can be demonstrated by having the necessary resources to support capabilities, such as funding, infrastructure, and analytical software/hardware. Furthermore, having skilled personnel, such as data analysts and scientists, to interpret and analyze the data is also a key aspect of readiness. More importantly, it is essential to create a culture of continuous learning and development in banks aiming to leverage big data (Horani et al., 2023). Readiness refers to the state required to adopt a particular innovation or engage in a particular activity (Jöhnk et al. 2021). This is the readiness of organizational and technological capabilities to extract value from data that will give them a competitive advantage. However, banks face significant challenges in understanding the potential to extract value from the data/information collected. These challenges resist big data analytics implementations due to behavioral and organizational

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issues and ambivalence in understanding the potential benefits (Raut et al., 2021). Organizations' efforts to successfully initiate and implement transformational change largely depend on adequate preparation before the implementation phase, known as readiness to change (Antony et al., 2023).

H1: As organizational barriers to big data analytics increase, the construction of a data-driven culture decreases.

Organizational readiness can be defined as a vital factor that facilitates the adoption of business analytics. According to Maroufkhani et al. (2023), organizational readiness for big data is defined as the availability of adequate financial resources, information technology infrastructure, and a skilled workforce that can effectively implement and use the technology. However, it can also be measured based on various factors including but not limited to these. In the field of big data and business analytics, researchers agree that organizational readiness is a critical prerequisite for the implementation of business analytics (Lutfi et al., 2022; Horani et al., 2023). Organizational readiness theory assumes that a higher level of organizational readiness increases the success of innovation adoption and reduces the risk of failure (Jöhnk et al., 2021). This study suggests that commercial banks will not be able to use business analytics effectively if they lack sufficient financial resources, a robust technological infrastructure, and qualified personnel. The literature on organizational readiness and change by Antony et al. (2023) suggests that organizations should have certain readiness factors such as leadership and top management support, an organizational culture that embraces change, employee buy-in, awareness of the change initiative, and customer and supplier buy-in (Antony et al., 2023). Furthermore, the biggest barrier to big data is stated as “non-specialized staff and inability to hire big data experts” (p.11) through the Big Data Analytics survey conducted by Russom (2011) (TDWI-The Data Warehousing Institute). Regarding the organizational context, managerial barriers have a significantly negative impact on the adoption and absorption of business analytics (Nam et al., 2019). Accordingly, our hypothesis is:

H2: Business analytics adoption decreases as organizational barriers to big data analytics increase.

Given the volume of data in use, firms need to transform their organizational culture into a data-driven culture. It has been stated that the adoption of business analytics positively affects a data-driven culture and that a data-driven culture encourages the use of business analytics (Hurbean et al., 2023). The ability of an analytical effort to create real business value in an organization is related to changes in organizational culture. In other words, business analytics studies show the support of a data-driven culture in realizing business value (Cao and Duan, 2014). The adoption of business analytics can directly improve an organization's data-driven culture. It can also strengthen the absorption and use of resources in the organization (Duan et al., 2020). A data-driven decision culture in an organization is crucial for the execution of business analytics; in particular, firms, where organizational leaders place great emphasis on data-driven decisions, are likely to adopt business analytics. On the contrary, the absence of a data-driven culture and insufficient top management support reduce the likelihood of business analytics adoption and assimilation (Nam et al., 2019).

H3: Business analytics adoption positively and significantly influences data-driven culture.

Recently, organizations have embraced the idea that data has become a core asset, and this belief is changing the culture of the organization; data and analytics now define a data-driven culture, leading to more effective data-driven decisions (Hurbean et al., 2023). As big data has become an essential resource for value creation, big data analytics requires the effective use of business analytics to capture, store, and analyze data for any change (Pappas et al., 2018). Data and analytics are used to modernize existing products, services, and processes to produce new products, services, and business models (Almazmomi et. al., 2022). As the banking sector is a data-intensive industry, one of the main benefits of business analytics applications in banking is the primary candidate for the skills to tackle complex real-world problems (Mohammed et al., 2024). According to Abubakar et al. (2024), the simultaneous presence of a complementary relationship between business analytics capabilities and π-shaped skills is found to indirectly influence innovation outcomes by fostering a data-driven culture. Business analytics practices foster critical interdependencies between inputs, processes, and outcomes. Therefore, business analytics can improve data use when adopted appropriately (Aydıner et al., 2019). As a way to overcome big data barriers to organizational readiness, the adoption of business analytics practices can have a complementary or fully mediating role. The links between the big data barriers to

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organizational readiness and the relationship between data-driven culture and the inclusion of business analytics adoption were investigated. Accordingly, our hypothesis is as follows:

H4: Business analytics adoption acts as a mediator in the relationship between organizational barriers to big data analytics and data-driven culture.

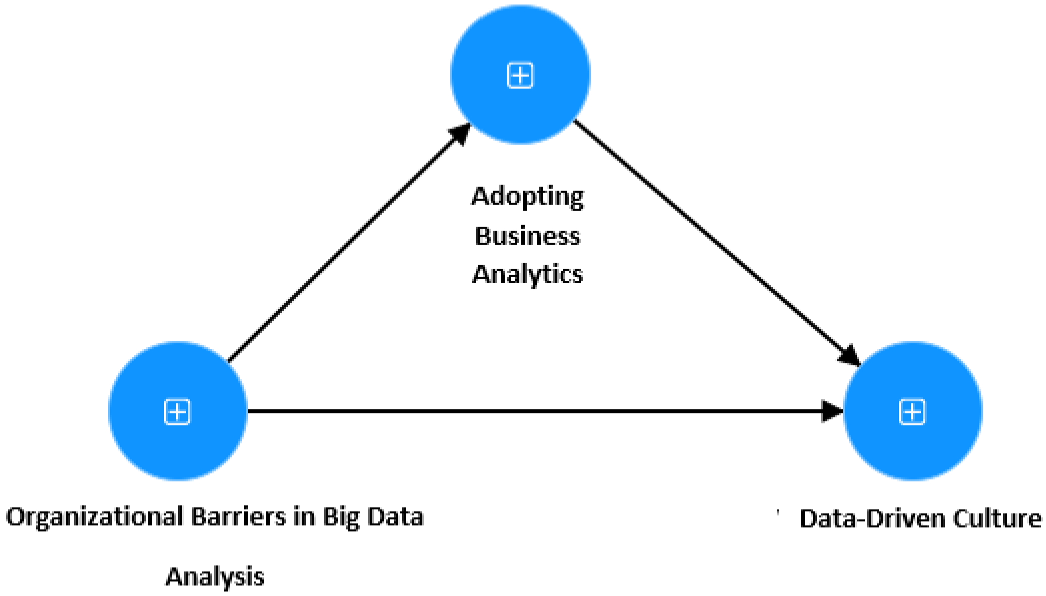

FIGURE 1 – CONCEPTUAL MODEL OF THE RESEARCH

6. RESEARCH METHODOLOGY

This study assesses the readiness of an organization to use big data, emphasizing that organizational readiness can be observed at multiple levels. These levels can be individual, team, department, or organizational (Lokuge et al. 2019). This study addresses big data barriers to organizational readiness at the organizational level. Therefore, this study defines organizational readiness for big data as “an organization's assessment of its readiness to use big data”. In this section, sample selection, development of the data collection tool, data collection process, and statistical methods and techniques used in data collection are explained. The data obtained were analyzed using appropriate SPSS 25.0 and SmartPLS 4 package programs. First, the data obtained from the participants were transferred to SPSS and organized. Then, the reliability and validity of each variable in the research model created in the SmartPLS4 program were tested. Secondly, the factor structure and factor relationship of the variables were tested while establishing the relationship between the latent variables (entrepreneurial orientation, firm performance, strategic improvisation). Necessary adjustments were made to ensure the best fit of the structural equation model to the relationship between the variables, thus increasing the relevance and effectiveness of this study.

6.1. Research population and sample selection

Banking operations have been affected by the emergence of data-driven technology systems that involve the capture and storage of massive amounts of data in unprecedented volume, velocity, and variety (Hasan et al., 2023). Therefore, the population of the study consisted of 376 bank employees in Ardahan and Kars provinces (Turkey). The sample size needed for the study is 190 (https://www.surveysystem.com/sscalc.htm). Accordingly, a questionnaire was applied to 232 employees from the population and 193 valid questionnaires were evaluated. The response rate was 83%.

6.2. Creating the questionnaire form

Business analytics adoption and data use culture scales among the scales that make up the questionnaire are taken from the study titled "Does data-driven culture impact innovation and performance of a firm? An empirical examination" by Chatterjee et al. (2024). Business Analytics Adoption is a 5-item scale and data-driven culture is a 4-item scale. The Organizational Barriers in Big Data Analytics scale is a 4-item scale taken from Daniel Q. Chen et al., (2015) "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management". All the scales used in the research are unidimensional. The scales that are used are five-point Likert-type scales. The Business Analytics Adoption and Data-driven Culture scales are in the range of (1) Strongly disagree and (5) Strongly agree, while the Organizational Barriers in Big Data Analytics scale is in the range of (1) does not hinder at all and (5) greatly hinders. The questionnaires, originally developed in English, were translated into Turkish by two experts in the field through translation and back translation. First, a pilot study was conducted with 46 employees, and the unidimensional structures of the scales and the significance of the statements in the scale were tested.

6.3. Results on demographic characteristics

The sample consists of 69.4% men and 30.6% women. It should be noted that 59.1% of the respondents were between the ages of 31 and 40, while 24.9% were under the age of 30. Furthermore, 2.1% of the respondents are older than 51 years. In terms of educational background, 12.4% of the participants graduated from primary and high school, 68.9% are undergraduates, and 18.6% are postgraduate. 61.1% of the participants work in public banks and 38.9% in private banks. In terms of work experience, 23.3% have up to 5 years of experience, 30.6% 6-10 years, 27.5% 11-15 years, 12.4% 16-20 years and 6.2% 21 years and above.

TABLE 1 – DEMOGRAPHIC STATISTICS

Variables	Frequency	Percent	Variables	Frequency	Percent
Gender			**Type of banking**		
Male	134	69,4	Private	75	38,9
Female	59	30,6	Public	118	61,1
Age group			**Job experience**		
≤ 30	48	24,9	≤ 5 year(s)	45	23,3
31-40	114	59,1	6-10 years	59	30,6
41-50	27	14,0	11-15 years	53	27,5
>51	4	2,1	16-20 years	24	12,4
Educational level			>21 years	12	6,2
High school and lower	24	12,4			
Undergraduate	133	68,9			
Graduate	36	18,6			

6.4. Measurement model

An exploratory factor analysis was conducted to test the construct validity of the scales and outlier loadings that distorted the factor loadings were removed from the analysis. These values were VK4 for the data-driven culture scale and IAB5 for the Business Analytics Adoption scale. Furthermore, the Variance Inflation Factor (VIF) was examined to assess the multicollinearity problem in the data. A VIF value of 5 or more indicates a multicollinearity problem among the indicators. The appropriate VIF value should be close to 3 or lower (Purwanto, 2021). Table 2 shows that there is no multicollinearity problem. Furthermore, a blend one-factor test was used to measure common method bias in the study (Podsakoff et al., 2003). The total variance explained is 47%, which is lower than the recommended standard (50%). This means that there is no significant problem of method bias in the data. Internal consistency coefficients for overall measurement and convergent validity, validity, and reliability of each construct are given in Table 2. The table shows that the AVE value of the model for all constructs is higher than the recommended AVE limit value of 0.5. The composite reliability values are between 0.809 and 0.869, and Cronbach's alpha and rho_A values are above the limit value of 0.70 (Hair Jr et al., 2020). Also, the correlational values of the variables are shown. The relationship between organizational barriers for big data analytics and data-driven culture and business analytics adoption (r = -0.340 and r = -0.344) is negative and significant. The relationship between data-driven culture and business analytics adoption is positive and significant (r = -0.869).

TABLE 2 – CORRELATION, FACTOR LOADS, DISCRIMINANT VALIDITY

Factors	1	2	3	Construct	Factor Loads	VIF	α	rho_A	CR	AVE
1. Organizational barriers on big data analytics				BV1	0,767	1,545	0.840	0.849	0.893	0.677
				BV2	0,873	2,335				
				BV3	0,862	2,156				
				BV4	0,784	1,781				
2. Data-driven culture	-0,340**	1		VK1	0,801	1,628	0.809	0.819	0.887	0.724
				VK2	0,851	1,790				
				VK3	0,897	2,144				
3. Business analytics adoption	-0,344**	0,869**	1	İAB1	0,883	2,568	0.869	0.876	0.910	0.718
				İAB2	0,803	1,927				
				İAB3	0,841	2,154				
				İAB4	0,860	2,366				

**$p < 0.01$

The Fornell-Larcker test was used to assess the discriminant validity. According to the requirements of discriminant validity, the square root of AVE should be greater than the correlation between the latent variables for each latent variable (Fornell and Larcker, 1981). In the diagram in Table 3, the AVE root values are 0.823, 0.869, and 0.851. AVE root values are larger than the correlation value between these numbers 0.340, 0344, and 0.847. Therefore, according to Fornell Lacker's criteria, the analysis meets the requirements of discriminant validity.

TABLE 3 – FORNELL-LARCKER CRITERIA FOR DISCRIMINANT VALIDITY

	Organizational barriers on big data analytics	Data-driven culture	Business analytics adoption
Organizational barriers on big data analytics	0.823		
Data-driven culture	-0.340	0.869	
Business analytics adoption	-0.344	0.847	0.851

Another criterion related to the measurement of divergence validity is the Heterotrait-Monotrait Ratio (HTMT) value. Based on the results of previous research, Henseler, Ringle and Sarstedt (2015) suggest a threshold value of 0.90 if the constructs are conceptually very similar and 0.85 if the constructs are conceptually more different. That is, an HTMT value that exceeds the relevant threshold for two constructs indicates a lack of dissociation (Ringle et al., 2023). As seen in Table 4, all the HTMT values in this sample are below the 0.85 criterion, indicating that there is no problem with discriminant validity.

TABLE 4 – HETEROTRAIT-MONOTRAIT (HTMT) CRITERIA

	Organizational barriers on big data analytics	Data-driven culture	Business analytics adoption
Organizational barriers on big data analytics			
Data-driven culture	0.412		
Business analytics adoption	0.394	0.795	

6.5. Structural model analysis

The following steps should be followed to assess the positive and significant mediating role of a structure (Preacher and Hayes, 2008; Shujahat et al., 2019): First, the total effect of the independent variable on the dependent variable and the corresponding significance value should be evaluated (Table 5). Second, if the value found is significant, the indirect effect (the effect of the independent variable on the dependent variable through the mediating variable) should be evaluated (Table 6). If it is significant, there is a possibility of either full or partial mediation. Otherwise, there is no mediation. Finally, to assess whether there is full or partial mediation, the direct effect of the independent structure on the dependent structure should be assessed (Table 7; Figure 2). If it is significant and the value of the path coefficient decreases compared to the total effects, partial mediation is present. Otherwise, there is full mediation. Based on these steps, the hypotheses are tested respectively.

TABLE 5 – TOTAL EFFECTS

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Organizational barriers on big data analytics -> Data-driven culture	-0.375	-0.378	0.081	4.607	0.000
Organizational barriers on big data analytics --> Business analytics adoption	-0.383	-0.387	0.087	4.400	0.000
Business analytics adoption --> Data-driven culture	0.841	0.842	0.038	22.251	0.000

In H1, it is asserted that as organizational barriers to big data analytics increase, the building of a data-driven culture will decrease. The total effect of organizational barriers to big data analytics on the decrease in building a data-driven culture as organizational barriers to big data analytics increase is negative and significant (β = -0.375, $p< 0.05$; Table 5). Therefore, H1 is accepted.

In H2 it was asserted that as organizational barriers for big data analytics increase, the adoption of business analytics will decrease. The total effect of the hypothesis that the higher the organizational barriers for big data analytics, the lower the adoption of business analytics is negative and significant (β = -0.383, $p< 0.05$; Table 5). Therefore, H2 is accepted.

In H3, it is asserted that the adoption of business analytics has a positive and significant effect on data-driven culture. The total effect of business analytics adoption on data-driven culture is positive and significant (β = 0.841, $p< 0.05$; Table 5). Therefore, H3 is accepted.

In H4, it is asserted that business analytics adoption plays a mediating role in the relationship between organizational barriers to big data analytics and data-driven culture. The indirect effect of organizational barriers concerning big data analytics on data-driven culture is negative and significant through business analytics adoption (β = -0.322, $p < 0.05$; Table 6). Therefore, either full or partial mediation is possible. The direct effect was then assessed. The direct effect of organizational barriers to big data analytics on data-driven culture is negative and insignificant after including business analytics adoption as a mediating variable (β = -0.053, $p > 0.05$; Table 7; Figure 2). Therefore, the effect of organizational barriers for big data analytics on data-driven culture becomes insignificant after the mediating variable enters the model. Thus, full mediation is concluded and H4 is accepted. Furthermore, the strength of the mediating structure should be tested after confirming the significance of the direct effect (Table 7) and the indirect effect (Table 6). This assessment can be performed by using VAF (variance accounted for), which is the variance calculated by dividing the indirect effect by the total effect. This method is among the methods used to test the strength of the mediation effect. A VAF value higher than 0.80 is considered full mediation; a VAF value between 0.20 and 0.80 is considered partial mediation, and a value less than 0.20 is considered no mediation (Sönmez Çakır, 2019; Meher et al., 2024). While calculating the VAF value; the VAF= Indirect effect/Total effect equation was used. Accordingly, the VAF value for H4 was calculated as VAF = 0.322/0.375 = 0.86. The full mediating role of business analytics adoption is thus confirmed.

TABLE 6 – DIRECT EFFECTS

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Organizational barriers on big data analytics --> Business analytics adoption--> Data-driven culture	-0.322	-0.326	0.076	4.228	0.000

TABLE 7 – INDIRECT EFFECTS

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Organizational barriers on big data analytics -> Data-driven culture	-0.053	-0.051	0.053	0.988	0.323
Organizational barriers on big data analytics --> Business analytics adoption	-0.383	-0.387	0.087	4.400	0.000
Business analytics adoption --> Data-driven culture	0.841	0.842	0.038	22.251	0.000

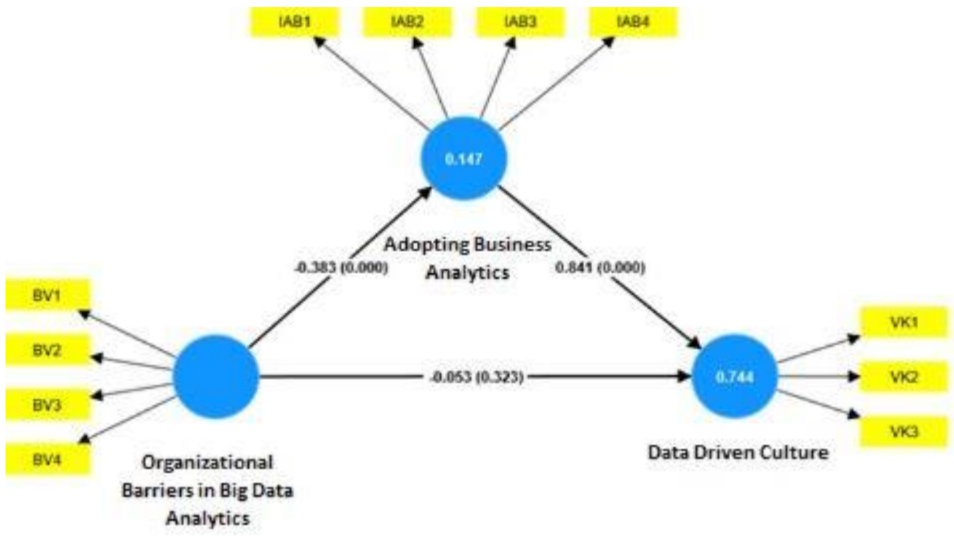

FIGURE 2 – STRUCTURAL MODEL

The responses of the employees to the open-ended question "What are the obstacles that prevent your business unit from fully utilizing big data analytics?" are shown. Considering the cases where some employees hesitated to answer, most of the respondents state that the lack of qualified resources is the most important obstacle for big data analytics. Employees also stated that cultural barriers and technological inadequacies in banks are also important barriers to big data analytics.

TABLE 8 – BARRIERS ON BIG DATA ANALYTICS

Construct	Frequency	Percent
Technological deficiencies	12	21,4
Cultural barriers	17	30,4
Lack of qualified resource	27	48,2
Total	56	100,0

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Although there are different themes in the context of digital transformation, the barriers to organization design can be defined under four categories. These are economic/financial, cultural, technical, and lack of competence (Gupta, 2018; Orzes et al., 2020; Alalawneh and Alkhatib, 2021). Bank employees stated that the biggest barrier to big data analytics is the lack of effective managers and qualified employees. This is because banks do not exhibit the right qualifications for data management. It could be a lack of harmony between the lead and member, disagreement on goals, unwillingness to participate in the necessary data management, or the perception of adding another 'job' to their already busy day-to-day work. These worries and concerns should not be ignored but rather embraced in a change management process (Jochberger, 2023).
The main benefit for both the bank and the employees will be a data-driven culture with appropriate tools and technology. Employees will enjoy more harmonized ways of working and the bank will benefit from greater efficiency. However, the right culture of using data, including data management tools, analytics software, and cloud computing platforms, needs to be in place to achieve this. Being data-driven is about more than having the best tools and data. Above all, it means investing in skilled resources to use that data to drive decisions and set behaviors that drive meaningful outcomes for all stakeholders, from employees to top executives.
The most common barriers that firms face is managerial and cultural rather than data and technology (LaValle et al., 2011). Lack of skilled resources refers to a lack of managerial skills, cultural barriers, and top management support to manage organizational adaptation to information technology, including business analytics. Organizational resistance to change resulting from managerial barriers can play a role in inhibiting their willingness to learn new ways of working (Nam et al., 2019).

7. CONCLUSIONS

The adoption of big data analytics and business analytics in emerging economies is recognized as one of the most fruitful fields of exploration. The dominant paradigm examining big data adoption involves identifying the situational factors that facilitate or hinder information technology adoption decisions in organizations (Verma and Bhattacharyya 2017). With growing interest in investing in data initiatives, enterprise data is recognized as a strategic resource and a catalyst for developing innovation capabilities (Samarasinghe and Lokuge, 2022). As banks move towards digitalization, they need to use big data to offer valuable products to their customers, manage potential risks, detect fraudulent activities, and create efficient business models (Nobanee et al., 2021). The changes experienced in value creation with digitalization necessitate fast, accessible, and efficient operations that meet customer expectations (Yıldırım, 2020). In this context, our results show that specialized employees and managers with business analytics at every step of the operational process gain strategic importance. The banking sector should also accelerate important recruitment programs for the education and training of key personnel (Sagiroglu and Sinanc, 2013). Integrating business analytics into decision-making processes is crucial for organizations seeking to thrive in a data-driven world and paves the way for sustainable growth and success in an ever-evolving market (Wolniak and Grebski, 2023).
Big data analytics is an emerging set of technologies and business analytics models. Discussions on big data analytics have not yet reached the level of clarity and common understanding as more mature areas of business analytics (Verma and Bhattacharyya 2017). Therefore, the adoption of business analytics in the banking sector emerges as a business model used instead of big data analytics in our study. An atmosphere should be created where decision-makers prefer data-driven methods in decision-making and the information obtained from business analytics results should be reflected in the organization's strategies and business processes. This also implies the need to develop managerial skills and a skilled workforce for a sustainable implementation of business analytics (Nam et al., 2019).

7.1. Policy recommendations and managerial implications

Managing large amounts of data in banks must be better than in many industries. This is because they need to provide accurate and detailed personal information to their customers. A bank traces every transaction on each customer's account, along with the customer's credit history, credit card transactions, and behavior across online and face-to-face channels. Banks therefore store a large amount of business, transaction, and customer data. Therefore, the challenge for the banking industry is the problem of effectively managing the high volume and multidimensional data flow (He et al., 2023). Hence, the main questions of this study are to identify the factors that hinder the use and adoption of big data analytics by bank employees.

It is stipulated that the total amount of data created, captured, copied, and consumed globally will exceed 180 Zettabytes by 2025, and the market size for analytics software applications will exceed USD 18 billion in 2026 in a study conducted by Statista (2024a, b). Therefore, big data analytics and a culture of data-driven are crucial in banking activities. Data-driven services offered by banks are expected to work full-time by customers. However, current regulations will not work unless they bring a data-driven culture with managerial skills and technological advances (Hasan et al., 2023).

The lack of managers and employees with big data and business analytics skills is one of the biggest challenges faced by organizations looking to adopt big data. Lack of data analytics skills among existing employees can lead to misrecording information, losing valuable information, and limiting the value a business can derive from the data it captures (Alharthi et al., 2017). Having the power to combine big data analytics with business process workflow and at the same time having employees with the right skills is for digital transformation is required (Kalema and Mokgadi, 2017).

7.2. Limitations and suggestions for future research

As in similar studies, this study has limitations and various suggestions for the future. First, since our data set is cross-sectional, this study can only show contemporaneous relationships between variables. Analyzing longitudinal processes can expand the literature to better understand the relationships between variables. Therefore, future research should collect longitudinal data by conducting additional surveys to provide more insights into the organizational barriers to big data analytics and the adoption process of business analytics. Second, the current study focuses on emerging economies such as Turkey, examines the banking sector, and offers an important contribution for managers and employees in the banking sector. Although we obtained responses from the most knowledgeable respondents, future research should collect data from a larger sample to reduce potential bias and obtain more reliable results and conduct a qualitative study to develop a new theoretical perspective.

Finally, more studies should be conducted targeting sectors such as tourism, manufacturing, and transportation for more comprehensive results. However, the focus should be on comparisons in the service and manufacturing sectors within emerging economies. This study highlighted the conceptual structure of the variables by focusing on organizational barriers to big data analytics and the mediating role of data-driven culture and business analytics. Therefore, future research should be conducted using different variables to expand new relationships such as meaningful data management, innovation, and data analytics technology through regulatory mechanisms.

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