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Analyzing the Role of Big Data in Enhancing Organizational Adaptability

Ragaa Nasr Ahmed[1], Haitham Mohamed Essam[2*]

[1]The Arab Academy for Management, Banking, and Financial Sciences (AAMBFS), Cairo, Egypt
[2]Adjunct Faculty, ESLSCA University, Cairo, Egypt
Email: *Haitham.Essam@eslsca.edu.eg

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Abstract

The Main Objective of This Research: This research investigates the impact of Big Data Analytics (BDA) on organizational adaptability within the automotive sector in Egypt. The rapid technological advancements and increasing competition in the global automotive industry necessitate agile and adaptive organizational strategies. By leveraging BDA, automotive firms can gain valuable insights into market trends, consumer preferences, and operational efficiencies. ***Design/Methodology/Approach***: This research employs a descriptive approach. A survey of 11 manufacturing automotive companies in Egypt was conducted, and this research was gathered through questionnaires. Convenience sampling was the method used to choose the sample, and the data were analyzed using SPSS and Smart PLS programs. ***Findings***: The research came to the conclusion that big data analysis helps achieve the organizational adaptability dimensions. Specifically, big data analysis helps achieve Creating Change by 10% (R^2 0.10), Customer Focus by 13% (R^2 0.13), and Organization Learning by 25% (R^2 0.25), which is the highest of these dimensions. The results of this research have practical as well as theoretical consequences since they are anticipated to make valuable contributions in both fields. The implications of this research underscore the critical role of BDA in driving competitive advantage and organizational resilience in the Egyptian automotive sector.

Keywords

Big Data Analytics, Organizational Adaptability, Organizational Learning, Customer Focus, Change Creation

1. Introduction

Data has taken over the globe in the era of Industry 4.0. Online social networks

like Facebook, Twitter, and others produce enormous amounts of data, and consequently, the amount of data generated by wireless and other technologies is equally vast. This enormous volume of data is commonly referred to as "Big Data", a repository where different data types and dimensions are combined (Rahman et al., 2022). Because of the numerous advantages Big Data offers, particularly to the automotive industry, it garners significant interest from academics, researchers, vehicle manufacturers, environmentalists, and various other organizations (Ali et al., 2020). A review of existing literature indicates that publications concerning Big Data were minimal and showed little change between 2011 and 2014. However, the number of articles dramatically increased and continued to rise from 2014 to 2019. The volume of pertinent papers published in 2020 experienced a drop, likely influenced by the COVID-19 pandemic.

In this context of rapid data expansion and global disruption, organizational flexibility is fundamentally demonstrated by a company's ability to effectively foresee and adapt to the fluctuations of a dynamic environment. However, the situation is more intricate than this definition suggests (Boylan & Turner, 2017). Recognizing the importance of maintaining a consistent level of adaptability is crucial, as business executives understand that for long-term success, their organization must be capable of continuous change (Kovacova & Lewis, 2021). The challenge lies in ingraining adaptability and transformation into the very fabric of the company, rather than merely effecting a one-time organizational overhaul. This necessitates establishing a system or response mechanism to address any crisis that may arise, be it financial, technological, environmental, or health-related. Creating adaptive organizations is a vital task for successful leaders. Such organizations not only react quickly to changing environments by analyzing problems and devising workable solutions, but they also proactively plan for future shifts. Indeed, the only reliable indicator of an organization's adaptability is its sustained success in a dynamic environment (Ployhart & Turner, 2014).

The need to empower organizations for adaptation in the face of increasingly dynamic and demanding circumstances is one of the main problems facing leaders today (Uhl-Bien & Arena, 2018). The pandemic, as noted by Kovacova & Lewis (2021), has underscored the critical importance of companies being adaptable; however, even prior to the upheaval of 2020, business leaders grappled with various crises. Despite the dedication and effort leaders invest, many initiatives aimed at fostering adaptability often fail to materialize. Moreover, while organizational transformation is a byproduct of adaptability, effective organizational adaptation—especially planned change—requires pre-established techniques or frameworks (Boylan & Turner, 2017).

To harness the myriad benefits of Big Data and enhance organizational flexibility in such a volatile landscape, Big Data Analytics (BDA) has emerged as a crucial area of focus. Both academics and industry are keenly interested in BDA, defined as the ability to access, analyze, and manage massive volumes of data with robust information architecture to improve manufacturing organizations' performance

(Aydiner et al., 2019; Delen & Zolbanin, 2018; Malomo & Sena, 2017; Matthias et al., 2017; Srinivasan & Swink, 2018). This increasing interest is driven by BDA's potential to fundamentally reshape company strategies and enhance value creation, as highlighted by Wang et al. (2022), who note the research focus on how organizations leverage BDA to rethink their approaches.

Despite the growing recognition of Big Data's potential, senior leaders in every sector still question whether they are maximizing the value of the vast amounts of information present in their organizations (LaValle et al., 2010). While new technology enables more data collection than ever, many businesses are still looking for better ways to use that data to their advantage and stay competitive, continuously asking how to effectively create value. This confusion stems partly from the multifaceted nature of Big Data and the fact that not all its components are equally applicable across contexts (Shaltout et al., 2023). For instance, as the Internet of Things (IoT) evolves, intelligent manufacturing increasingly relies on gathering vast amounts of data. Nevertheless, significant challenges arise when attempting to fully leverage this data (Kusiak, 2017), hindering organizations from proactively planning and making more informed, data-driven decisions while maintaining adaptability and agility (Sushil, 2017).

Although the domain of Big Data attracts significant attention, information often remains fragmented in silos. There is a scarcity of literature that offers a comprehensive overview of the evolving knowledge in this domain, particularly concerning its application in enhancing organizational adaptability. While existing reviews emphasize Big Data's potential to drive competition, productivity, growth, innovation, and consumer surplus across industries through data exploration and utilization (Manyika et al., 2011; Zikopoulos et al., 2011; Xiang et al., 2015), the explicit link to fostering sustained organizational flexibility requires further exploration. The majority of earlier studies (Akter et al., 2016; Aydiner et al., 2019; Chen et al., 2015; Wamba et al., 2017) have primarily focused on how Big Data Analytics (BDA) affects an organization's overall performance (Dubey et al., 2019), often concluding that BDA use in complex decision-making leads to greater market competitiveness (Chen, 2014). However, fewer studies have specifically examined BDA's direct role in cultivating organizational adaptability, particularly in unique sectoral and geographical contexts. In summary, a closer look at the literature on Big Data Analytics and organizational adaptability reveals several shortcomings and gaps:

Firstly, there is a distinct scarcity of studies examining the direct effect of Big Data Analytics on organizational adaptability, specifically within the automotive sector in Egypt. This research is therefore expected to fill a crucial knowledge gap in this context. Secondly, current literature lacks a comprehensive set of practical recommendations for managers to enhance organizational adaptation, especially given the permanent changes in the work environment. Finally, existing research has not fully leveraged theoretical lenses such as the Resource-Based View (RBV) to explore the specific benefits derived from applying Big Data Analytics in achiev-

ing organizational adaptation. While some studies, like Dubey et al. (2019), have integrated theories such as RBV to investigate links between institutional elements and business performance, or how intangible resources like information sharing in BDA can enhance performance (Gunasekaran et al., 2016), a focused application of RBV to articulate how BDA specifically translates into organizational adaptability remains underexplored.

Thus, the primary objective of this research is to investigate the influence of Big Data Analytics on organizational adaptability within the Egyptian automotive sector, framed by the Resource-Based View. This research aims to provide both theoretical insights and practical recommendations for leaders navigating the complexities of the modern business environment.

2. Research Questions

This research is guided by the existing theoretical foundation in the literature, which provides direction for the research questions. The overarching aim is to investigate the influence of big data analytics on organizational adaptability. The specific research questions are as follows:

1) What is the effect of big data analytics on organizational adaptability within the Egyptian automotive sector?

2) How does big data analytics influence the process of Creating Change within the Egyptian automotive sector?

3) What impact does big data analytics have on enhancing customer focus within organizations in the Egyptian automotive sector?

4) How does the utilization of big data analytics affect organizational learning processes within the Egyptian automotive sector?

3. Research Objectives

To answer this research question, the paper aims to explore the impact of big data analytics on organizational adaptability. More specifically, the aims of this paper are:

1) To identify the impact of big data analytics on Creating Change within the Egyptian automotive sector.

2) To explore the impact of big data analytics on customer focus within the Egyptian automotive sector.

3) To illustrate the impact of big data analytics on organizational learning within the Egyptian automotive sector.

4. Theoretical Background and Development of Hypotheses

4.1. Big Data Analytics (BDA) and Organizational Adaptability

Big Data, as defined by Gartner Inc., refers to information assets characterized by high volume, velocity, and/or variety, demanding innovative and cost-effective approaches to information processing for enhanced insight, decision-making, and process automation (Rahman et al., 2022). This perspective acknowledges data as

a valuable asset that underpins economic value, requiring modern infrastructure and specialized expertise for its processing. Furthermore, leveraging such advanced approaches yields benefits, including new discoveries, improved decision-making processes, and increased automation (Bogdan & Borza, 2019).

Big Data Analytics (BDA), according to Davenport & Kim (2013), is "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions". Essentially, BDA transforms raw data into actionable insights through various statistical methods. Organizationally, it facilitates a new management paradigm that relies on evidence rather than intuition or past experience. BDA can be classified into descriptive, predictive, and prescriptive categories based on its scope. Big Data, fundamentally, refers to datasets marked by their immense volume, high velocity, and/or diverse variety, necessitating the adoption of new technologies and methodologies for their collection, storage, and analysis. Its primary purpose is to optimize processes and enhance decision-making. Notably, what is considered "large data" today may evolve significantly in the future (Watson, 2014). Wang et al. (2022) categorize BDA into three generations: the first tackles complex problems with simple algorithms; the second employs complex algorithms for intricate issues; and the latest generation aims for human-like intelligence through advancements in Artificial Intelligence (AI).

Adaptation, fundamentally, denotes a response to environmental changes (Boylan & Turner, 2017). The necessity for organizational adaptation is an integral principle in organization studies, a concept emphasized since the earliest writings of scholars like Barnard, Simon, Selznick, and Thompson, all of whom underscored the imperative for organizations to adjust in accordance with their evolving environments. Given its paramount importance, this topic has been extensively explored across a broad spectrum of literature, yet the sheer volume of scholarly work has often resulted in fragmented insights, each shaped by particular disciplinary perspectives (Uhl-Bien & Arena, 2018). In contemporary times, researchers in organizational theory, strategic management, and business management consistently devote significant attention to the issue of organizational adaptation to the environment (Ramesh et al., 2023).

Regarding organizational adaptability, Chandler Jr (1998) posits that a crucial first step in developing corporate strategy is to evolve with the times. Bennis (1966) further contends that organizations must continually adapt to their external environments and actively engage their members in coordinating operations and maintaining organizational systems. From a capabilities perspective, Chowdhury (2005) defines an organization's flexibility as its capacity for learning and changing.

Organizations demonstrate adaptability through both their planning and execution phases. During planning, agility is shown by anticipating issues before they arise. Proactive adaptability is evident when organizations create choices that account for the non-linearity of the operating environment. This foresight and de-

velopment of multiple options significantly reduces reaction time to environmental changes. Adaptable organizations effectively avoid sunk cost fallacies, which could otherwise lead to adherence to a plan beyond its point of no return (Boylan & Turner, 2017).

4.2. Resource-Based View Theory

Resources are classified according to RBV logic as organizational, human, and physical capital. The Resource-Based View (RBV) classifies resources as organizational, human, and physical capital (Barney, 1991). Other categories, including financial, technological, and reputational capital, have also been recognized (Grant, 1996). Mailani et al. (2024) define resources as assets a company either owns or can access. These can be tangible, such as infrastructure, or intangible, like information or knowledge sharing (Dubey et al., 2019).

From an RBV perspective, Big Data Analytics capabilities can significantly enhance organizational adaptability by fostering collaboration, which is a primary source for generating flexibility (Srimarut & Mekhum, 2020). Big Data, as articulated by Shaltout et al. (2023), facilitates novel techniques for continuous real-time monitoring and feedback, potentially leading to new accountability and reward structures within organizations. Furthermore, Dubey et al. (2019) contend that while Big Data is a relatively recent phenomenon, advanced analytics, on which BDA relies, is a discipline rooted in years of statistical research and scientific application, building upon past experiences with data-driven manufacturing processes. Consequently, BDA serves as an essential tool for achieving yield increases, particularly in industrial environments characterized by process complexity, variability, and capacity limits.

Big Data Analytics (BDA) must be viewed as a strategic organizational resource assessed using the VRIO framework in order to fully implement the Resource-Based View (RBV) (Barney, 1991; Barney & Clark, 2007). BDA skills add value by helping businesses improve operational performance, boost forecasting accuracy, and facilitate evidence-based decision-making—qualities that are essential in highly dynamic, technology-driven industries like the automotive sector (Wamba et al., 2017).

In the Egyptian automotive sector, where digital transformation is still uneven and only a small number of companies have the technological infrastructure and trained analytics workforce required to fully utilize data-driven insights, these capabilities are also comparatively rare (Mikalef et al., 2020). Additionally, because BDA resources rely on proprietary datasets, accumulated analytical skills, and ingrained organizational procedures that are difficult for rivals to copy, they demonstrate significant imitability (Gupta & George, 2016). Lastly, companies that make investments in complementary organizational structures—like cross-functional integration, analytical skills, and governance mechanisms—show that they are prepared to turn BDA capabilities into long-term competitive advantage (Braganza et al., 2017).

Through this VRIO-based interpretation, BDA emerges not merely as an operational tool but as a strategic resource that strengthens organizational adaptability in volatile environments such as the Egyptian automotive sector.

Moreover, the availability of sensor data in manufacturing enables real-time equipment monitoring and facilitates the early identification of issues (Tiwari et al., 2018). A significant benefit of utilizing Big Data lies in the enhancements to corporate reporting, especially through dynamic, real-time updates that boost accuracy. BDA, in this redesigned corporate reporting, analyzes large amounts of rapidly changing data to deliver timely information, thus meeting stakeholders' needs (Mello & Martins, 2019). Manufacturers can leverage this data to make well-informed decisions regarding production and inventory, sales forecasting, optimizing commodity prices, managing inventory, streamlining logistics, coordinating with suppliers, forecasting demand, and enhancing services and customer satisfaction (Grover & Kar, 2017). In this context, Xu et al. (2015) state that Big Data analysis can convert unstructured, low-level data into actionable knowledge, scale effectively with increasing data volumes, and enhance adaptability and extensibility in the face of data diversity and unpredictability. Hence, grounded in the Resource-Based View, this paper proposes that:

H1: Big Data Analytics has a directly significant positive impact on Organizational Adaptability.

The novelty of Big Data Analytics arises from the convergence of new data sources (such as social media), emerging business opportunities, and technological and software advancements. This convergence fuels the current interest and future prospects for BDA, even giving rise to a new discipline, "data science", which encompasses the methods, tools, technologies, and procedures for interpreting massive datasets. BDA is currently transforming existing jobs and creating new ones (Watson, 2014). An organization's capacity to identify, initiate, and manage change is a crucial aspect of its overall adaptability. Given BDA's role in providing insights that highlight the need for change and inform its direction, it is posited to significantly influence this process.

H1.1: Big Data Analytics has a directly significant positive impact on Creating Change.

As many businesses transition from a historically product-centric orientation to a more customer-centric approach, focusing on retaining and developing profitable customer relationships, analyses across the customer lifecycle—including acquisition, retention, and expansion—have become a critical focus (Gupta et al., 2006). This customer focus is intrinsically linked to organizational adaptability, as it requires continuous adjustment to evolving customer needs and market demands. Big Data Analytics plays a vital role in this by ensuring efficient and rapid delivery of complex services to the client (Xu et al., 2015), thereby enabling organizations to better understand and respond to customer dynamics.

H1.2: Big Data Analytics has a direct, significant, positive impact on Customer Focus.

According to Grant's (1996) knowledge-based view of the firm, an organization's value is fundamentally constrained by the knowledge residing within it. Thus, the sustainable development of entire sectors, regions, and destinations is tied to the availability (and accessibility) of knowledge required to (re-)configure resources, especially knowledge-based resources, in order to maintain competitiveness (Gandomi & Haider, 2015). Resources are broadly defined as "the totality of assets, capabilities, organizational processes, information, and knowledge controlled by an organization that enable it to develop and put into practice strategies that increase efficiency and effectiveness" (Kogo & Kimencu, 2018).

However, in the long run, these resources will only offer competitive advantages if customers perceive them as valuable, limited, and challenging for rivals to copy and replace. If these requirements are met, the entrepreneurial activity of combining and reconfiguring resources will be founded on core competencies that must then be validated and updated through ongoing knowledge acquisition and learning procedures. The literature defines this "dynamic capability" as the ability to integrate, grow, and reconfigure internal and external competencies to handle changing contexts. Consequently, organizational learning is operationalized by two core competencies: the ability to efficiently replicate existing processes and operations (replication capability) and the ability to continuously change the configuration of existing resources by acquiring and developing new core competencies. Firm-internal knowledge transfer and associated codification processes are often the driving forces behind replication capabilities. Conversely, the ability to absorb outside knowledge and the capacity to draw generalizable cause-and-effect connections from previously learned information, applicable to a wider variety of strategic possibilities, primarily determine reconfiguration skills (Gandomi & Haider, 2015). Given that BDA fundamentally enhances an organization's capacity to acquire, process, and interpret vast amounts of information, it serves as a powerful catalyst for both replication and reconfiguration capabilities, thereby directly impacting organizational learning processes.

H1.3: Big Data Analytics has a direct, significant, positive impact on Organizational Learning.

Finally, according to the previous studies, the research model shown in **Figure 1** indicates the aims of this research, which state how BDA could enhance organizational adaptability. The model, which is based on the Resource-Based View (RBV), views BDA as the main independent variable, and three important dependent variables—Creating Change, Customer Focus, and Organizational Learning—that are taken from Denison & Mishra's (1995) organizational culture and adaptability framework—serve as a representation of organizational adaptability.

5. Methodology

5.1. Research Design

Saunders et al. (2009) noted that research design includes three important types,

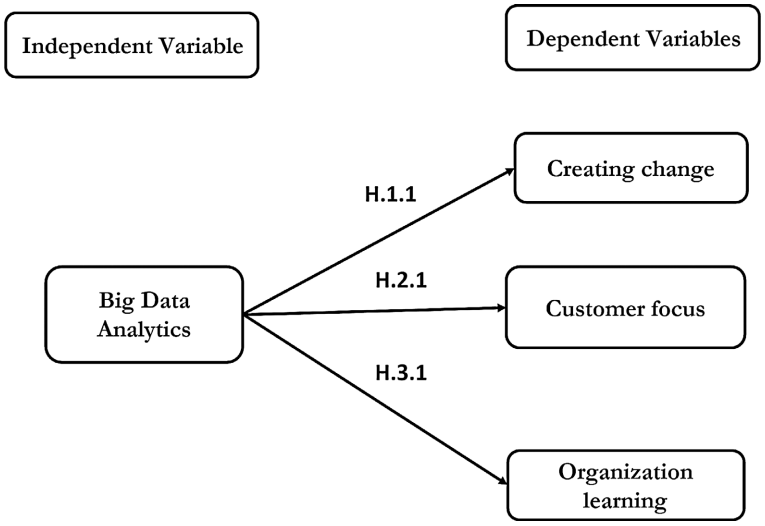

Figure 1. Research model.

namely descriptive, exploratory, and explanatory. "This research adopts a descriptive design to explore the relationships among the research variables and to provide structured insights into the influence of Big Data Analytics on organizational adaptability."

5.2. Data Collection, Types of Data

Both primary and secondary data were utilized in this research. Primary data were collected specifically for this research topic using a questionnaire. Conversely, secondary data, which had been previously published and used for purposes other than the current topic, were gathered from websites, theses, books, and articles discussing the research variables and related subjects.

5.3. Questionnaire Design

The current research explored the impact of big data analytics (independent variable) on organizational adaptability (dependent variable). This research employed the questionnaire-based survey method because it allows for generalizable outcomes, easy replication, and the simultaneous examination of numerous factors (Pinsonneault & Kraemer, 1993). The researchers focused on a variety of measurement items taken from previous studies. Also, the researchers prepared Arabic and English forms of the questionnaire to make it fully accessible to the entire targeted group, using a five-point Likert scale with choices ranging from "1 = completely disagree" to "5 = completely agree" to assess the measurement items.

The questionnaire was addressed to automotive company staff, including three sections containing 21 statements. The first section was designed to measure big data analytics as an independent variable and was adapted from the research of Kusumah et al. (2024). It is divided into three dimensions: Data availability, reflected in the statements (from DA1 to DA4); Technical skills, reflected in the statements (from TS1 to TS3); and Data-driven, reflected in the statements (from

DMC1 to DMC4).

The information about organizational adaptability that was gathered for the second section was edited and adapted from (Denison & Mishra, 1995), which is divided into three dimensions: Creating Change, reflected in the statements (from CC1 to CC3); Customer focus, in the statements (CF1-CF3); Organizational learning, reflected in the statements (OL1-OL3). Finally, the third section was designed to collect information about the targeted group demographics, reflected in the statements.

Because they capture fundamental aspects of organizational adaptability and Big Data Analytics (BDA) capabilities that are pertinent to technology-intensive and fiercely competitive industries, these tools are especially appropriate for the Egyptian automotive sector. For example, Denison's framework is suitable for analyzing internal dynamics inside automobile companies because it has been extensively used to evaluate organizational learning, adaptation, and change-creation processes in manufacturing and service industries. In a similar vein, the BDA scale created by Kusumah et al. (2024) offers a thorough evaluation of data-driven capabilities, which is consistent with the growing digital transformation programs in Egyptian automakers. Using these validated scales guarantees that the constructs are evaluated in a way that is consistent with earlier empirical research and improves measurement accuracy.

5.4. Questionnaire Pilot Testing

It is preferable to create a pilot survey as a pre-test for the data collection instrument, which is the questionnaire. Because of how quickly the research was conducted, the researchers were able to confirm the reliability and validity of the findings. Furthermore, the pilot survey might offer some recommendations for changes to the questionnaire (Kothari, 2004). Pilot surveys are therefore essential to enable data collection so that responses can be made promptly, easily, and without any difficulties.

5.4.1. Confirmatory Factor Analysis (CFA)

A common technique in scale development, validity analysis, and verifying a predetermined structure is confirmatory factor analysis. Using a previously developed model, this method creates a latent variable (factor) based on the observed variables (Yaşlıoğlu, 2017). In the CFA, SmartPLS 3 software was utilized. The measurement model was assessed using CFA for convergent validity, discriminant validity, and indicator and internal consistency reliability (Composite Reliability), by utilizing SmartPLS 3 to execute the PLS algorithm.

During the Confirmatory Factor Analysis (CFA), three items were removed from the measurement model due to their insufficient factor loadings. The model was recreated (**Figure 2** and **Figure 3**). Following established methodological guidelines, a minimum loading threshold of 0.50 was adopted, as recommended by Hair et al. (2019), to ensure that each indicator adequately represented its underlying construct. Items that did not meet this criterion were excluded to

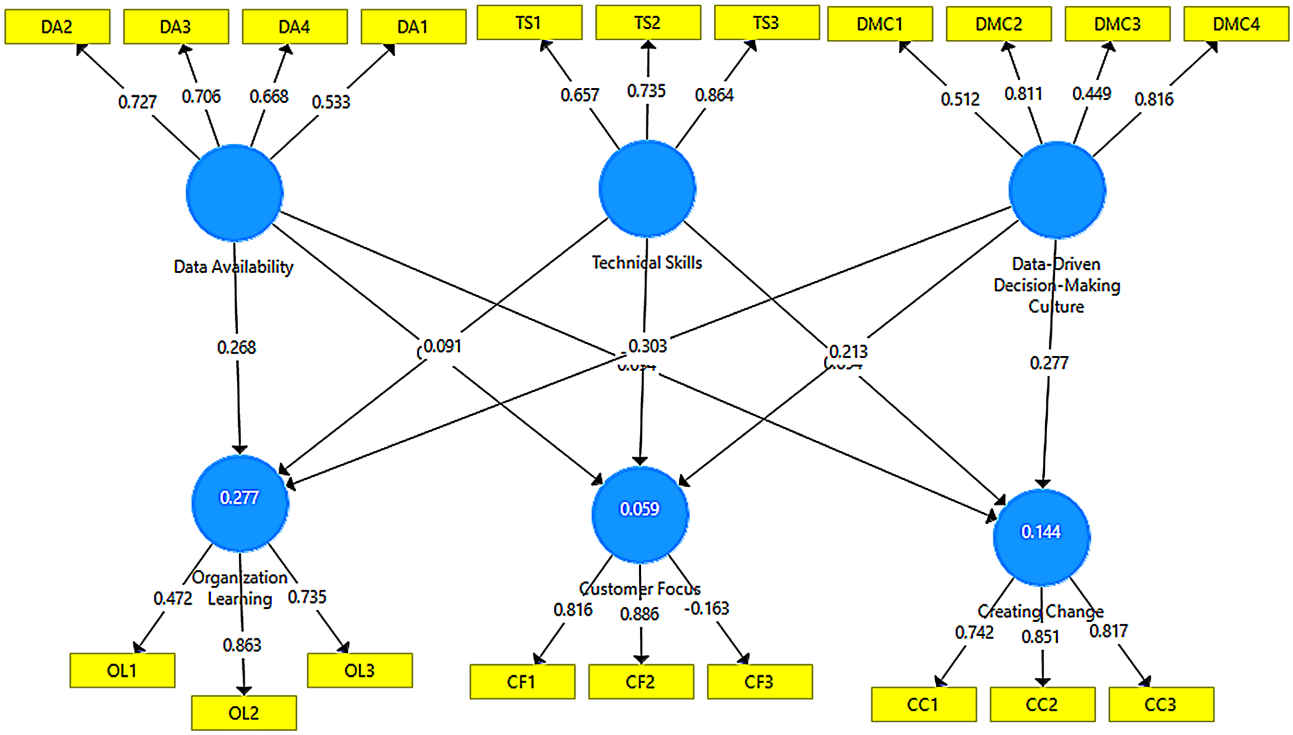

Figure 2. First measurement model.

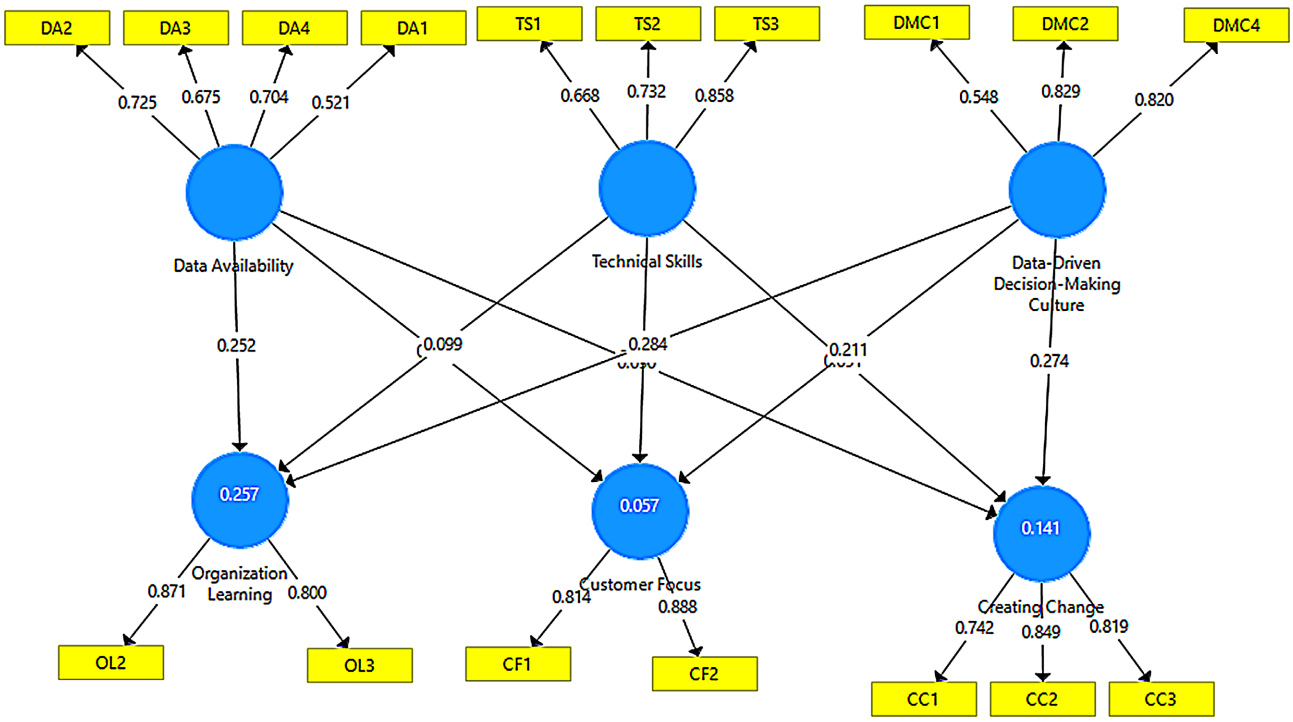

Figure 3. Revised measurement model.

enhance the convergent validity and overall reliability of the measurement model. Applying this threshold strengthened the model's psychometric properties and ensured that only the most theoretically and statistically robust items were re-

tained for subsequent analysis.

5.4.2. Convergent Validity and Reliability

First, the convergent validity test was merged with the outer loading of indicators (factor loadings) to perform the internal consistency (composite) reliability test using Cronbach's alpha. The Average Variance Extracted (AVE) values were taken into consideration in order to verify convergent validity. Composite reliability is used to verify internal consistency, and a value of more than 0.70 is anticipated, while Cronbach's alpha is the analysis's criterion. The indication reliability is referred to as outer loading, and it should be more than 0.500. On the other hand, indicators with outer loadings more than 0.40 need to be eliminated if they do not raise the composite reliability and AVE threshold values (Hair et al., 2019). Convergent validity requires an AVE of at least 0.50. According to **Table 1**, the convergent validity of the model was confirmed.

On the other hand, according to Hair et al. (2019), the value of Cronbach's alpha, which should be equal to or greater than 0.7 in order to have a credible questionnaire, is the most widely used indication of reliability. The following table shows that the values of Cronbach's alpha are above 0.750, which means the questionnaire is reliable.

Table 1. Convergent validity values.

Variables	Factors	Outer Loadings	AVE	Composite Reliability	Cronbach's Alpha (α)
Data availability	DA1	0.521	0.537	0.754	0.794
	DA2	0.725			
	DA3	0.675			
	DA4	0.704			
Technical skills	TS1	0.668	0.573	0.799	0.735
	TS2	0.732			
	TS3	0.858			
Data-driven decision-making culture	DMC1	0.548	0.553	0.783	0.701
	DMC2	0.829			
	DMC4	0.820			
Creating Change	CC1	0.742	0.647	0.846	0.734
	CC2	0.849			
	CC3	0.819			
Customer focus	CF1	0.814	0.725	0.840	0.725
	CF2	0.888			
Organization learning	OL2	0.871	0.699	0.823	0.673
	OL3	0.800			

5.5. Population and Sample

5.5.1. Population

Eleven Egyptian automotive companies met the research's demographic requirements. Due to their representativeness in the local market, eleven Egyptian automakers were chosen as the research population. These businesses come in a variety of sizes and specializations, such as distributors, authorized dealers, and assembly companies. This choice represents the variety of managerial and technological techniques associated with the application of Big Data Analytics (BDA) in the industry and enables thorough coverage of organizational operations. By concentrating on these companies, it is also possible to gather precise information from managers and staff who are directly involved in organizational adaptation and decision-making processes.

In order to guarantee that the sample was appropriate for analyzing the effect of BDA on organizational flexibility, the chosen organizations were selected according to particular criteria. These factors included the firms' willingness to take part in research, the availability of structured organizational data, and their degree of involvement with digital transformation programs. The research guarantees that the data gathered appropriately reflects the relationship between BDA skills and organizational flexibility in the Egyptian automotive sector by focusing on businesses that actively use data-driven processes.

5.5.2. Sample Technique

Due to the challenges in obtaining a sample frame, the researchers in this research used a non-probability sample. The researchers used convenience sampling, a non-probability sampling method in which samples are chosen from the population solely based on the researcher's convenience.

5.5.3. Sample Size

The respondents of this survey (N = 384). Only employees and managers from the eleven participating automakers made up the research sample. Because they have firsthand experience with internal organizational processes, such as learning mechanisms, change-creation activities, and customer-oriented practices, these respondents were specifically chosen. As a result, information gathered from those directly involved in and accountable for internal decision-making and operational operations served as the foundation for all assessments pertaining to organizational flexibility. The sample is now correctly in line with the research's theoretical framework, research goals, and measurement constructs thanks to the updated description.

5.5.4. Sample Profile

Frequency analysis was employed in this research to describe the respondents' characteristics, highlighting their age, gender, and work status, among other sociodemographic features. Regarding this, the actual sample structure that was examined for the respondents is shown in **Table 2**.

Table 2. Sample distribution.

Frequency		Percent
Gender		
Male	299	85%
Female	53	15%
Total	352	100
Age		
(20 - 29)	19	5%
(30 - 39)	251	71%
(40 - 49)	51	15%
(50 - 59)	31	9%
Total	352	100
Employment level		
Managerial Level	282	80%
Directors Level	70	20%
Total	352	100

Regarding the gender distribution of the sample, respondents who identified as male made up 85% of the sample, while respondents who identified as female made up 15% of the sample. This indicates that men make up the majority of the managers in the research population. In terms of the sample's age distribution, 71% of the sample's participants were between the ages of 30 and 39. This indicates that the majority of administrative workers are young, with 15% of respondents being between the ages of 40 and 49. Of the sample, 9% of respondents were 50 years of age or older, while just 5% were between the ages of 20 and 29. When it came to the sample's employment distribution, 80% of the respondents were at the management level, followed by 20% of respondents at the director level.

6. Data Analysis

6.1. Descriptive Analysis

The descriptive analysis shows information about the variable, indicating the nature of the variable. For the independent and dependent variables, descriptive statistics such as means and standard deviations were acquired. The means and standard deviations for each variable were used in the current investigation. A five-point rating system was used to assess each variable. Data availability, one of the independent support variables shown in Table 3, had a mean score of 3.90 and a standard deviation of 0.567. The mean score for technical skills was 3.46, with a standard deviation of 0.727, and with a standard deviation of 0.602 and a mean score of 3.71 for the culture of data-driven decision-making.

Table 3. Descriptive analysis.

Variables		Mean	Std. Deviation	Skewness		Kurtosis	
				Std. Error	Statistic	Std. Error	Statistic
Big Data Analytics	Data availability	3.90	0.567	0.130	−1.251	0.259	3.423
	Technical skills	3.46	0.727	0.130	−0.604	0.259	0.873
	Data-driven decision-making culture	3.71	0.602	0.130	−0.313	0.259	0.120
Organizational Adaptability	Creating Change	3.71	0.699	0.130	−1.019	0.259	1.916
	Customer focus	3.09	0.536	0.130	−0.034	0.259	1.191
	Organization learning	3.69	0.609	0.130	−0.656	0.259	1.200

While the dependent sup variables, which are Creating Change, had a mean score of 3.71 with a standard deviation of 0.699. Customer focus had a mean score of 3.09 with a standard deviation of 0.536. Organization learning had a mean score of 3.69 with a standard deviation of 0.609.

Eventually, the normal distribution assumption can be reached when the skewness and kurtosis are equal to zero. However, in the ongoing research data, the skewness and kurtosis for each item are not equal to zero. Thus, the assumption of normal distribution is not strictly met. However, the skewness and kurtosis values fall within acceptable ranges, indicating that this does not significantly threaten the validity of the results (Kline, 2015).

However, scholars have mentioned that the violation of the normal distribution assumption commonly happens in data collected from individuals, such as in social sciences. Accordingly, the violation of the normality assumption does not have serious effects on the results when the skewness coefficient ranges between −3 and +3. Also, the kurtosis coefficient should range between −10 and +10 (Kline, 2015). Consequently, the skewness and kurtosis coefficients in the current research do not lead to serious effects on the results.

6.2. Correlations between the Variables

As can be clearly seen from Table 4, each of the dependent variables has a significant and positive relationship with each of the independent variables. This initially supports the proposed hypotheses.

6.3. Linear Regression

The aim of linear regression is to find a linear relationship to explain the correlation between an independent and possibly dependent variable. As shown in Table 5, Big Data Analytics has a significant effect on organizational adaptability dimensions. First, Big Data Analytics has a significant effect on Creating Change (β =

0.459, t = 6.184, sig = 0.000), Customer focus (β = 0.281, t = 3.592, sig = 0.000), and Organization learning (β = 0.755, t = 10.962, sig = 0.000). In other words, Big Data Analytics explains 10%, 13%, and 25% of the variances in Creating Change, Customer focus, and Organization learning.

Table 4. Person correlation.

		Big Data Analytics	Creating Change	Customer focus	Organization learning
Big Data Analytics	Pearson Correlation Sig. (2-tailed)	1			
Creating Change	Pearson Correlation Sig. (2-tailed)	0.314** 0.000	1		
Customer focus	Pearson Correlation Sig. (2-tailed)	0.189** 0.000	0.369** 0.000	1	
Organization learning	Pearson Correlation Sig. (2-tailed)	0.506** 0.000	0.269** 0.000	0.214** 0.000	1

**Correlation is significant at the 0.01 level (2-tailed).

Table 5. Linear regression.

	Creating Change	Customer Focus	Organization Learning
Beta	0.459	0.281	0.755
T value	6.184	3.592	10.962
Sig	0.000	0.000	0.000
R^2	0.10	0.13	0.256
S. E.	0.074	0.078	0.069

7. Research Implications

7.1. Theoretical Implications

- The research provides a theoretical framework that enriches the understanding of how BDA can foster organizational adaptability.
- It presents a model that can be applied across different industries to explore the relationship between BDA, innovation, and organizational change.
- The research draws on the Resource-Based View (RBV) theory as its primary analytical framework, demonstrating how BDA capabilities can enable organizations to respond quickly to environmental changes, drive innovation, and enhance operational flexibility.
- In both the public and business press, big data and analytics are subjects of interest. Books like Super Crunchers, as well as articles in periodicals like the New York Times, the Wall Street Journal, and the Financial Times (Watson, 2014), highlight this trend. For this reason, the researchers believe that there is a need to pay attention to studies in this field in the Middle East. Bridging a

Knowledge Gap. There is limited empirical research on the application of BDA in Egypt's automotive sector. This research addresses this gap by providing concrete evidence of the role of data-driven strategies in fostering organizational adaptability in this context.

- Framework for Future Research: The proposed model serves as a basis for further investigations into the relationship between big data, adaptability, and competitive advantage across different industries and regions.

7.2. Practical Implications

This research provides practical insights that can inform strategic decision-making within organizations, particularly in the following areas:

- Enhanced Operational Flexibility: The findings underscore the importance of integrating BDA into organizational processes to foster adaptability. Automotive companies can utilize BDA to improve responsiveness to market changes and enhance operational efficiency.
- Customer-Centric Strategies: The research highlights the role of BDA in refining customer focus by allowing companies to tailor their offerings to changing consumer preferences. This can be achieved by analyzing real-time data on customer behavior and feedback.
- Organizational Learning: The results demonstrate that BDA is a powerful tool for promoting continuous organizational learning, which, in turn, enhances the ability to innovate and remain competitive in a fast-paced environment.

8. Limitations of the Research

This research has limitations despite the insightful information it offers. First, the results' applicability to Egypt's larger automobile industry is restricted by the convenience sampling method. Second, long-term dynamics or changes in BDA practices are not taken into consideration by the cross-sectional design, which only records a moment in time. Third, using self-reported questionnaires could lead to answer bias since respondents might exaggerate how flexible or big data analytics-savvy their company is. Lastly, although the Egyptian automobile industry was the research's primary emphasis, without additional validation, the results might not be broadly relevant to other industries or regions.

9. Suggested Future Research

- Examine how BDA affects organizational flexibility in the Egyptian automobile industry in relation to other Egyptian and international industries. This can assist in identifying issues and best practices unique to a given industry.
- Conduct longitudinal studies to observe the long-term effects of BDA on organizational adaptability. This can help in understanding how BDA influences adaptability over time and how organizations evolve their use of BDA.
- Analyze how organizational culture affects the use and results of BDA. Possible research topics include how cultural perspectives on data and technology affect

adaptability and what cultural changes are required for the successful incorporation of BDA.

10. Conclusion

Big data analytics allows the industry to collect data from ERB systems and aggregate information from numerous functional units of the business and supply chain members. On this industry's manufacturing floor, robots, RFIDs, barcode scanners, and sensors are becoming increasingly widespread. The current research aimed to discover the expected impact of big data on organizational adaptability. The research relied on measuring and analyzing three dimensions of organizational adaptability (organizational learning, customer focus, and change creation) as applied to the automotive sector in Egypt. The research population included all managerial levels in the Egyptian automotive sector.

Hence, we employed the Resource-Based View theory (RBV) (Barney, 1991). The RBV places a strong emphasis on how internal resources affect organizational performance and tactics (Barney, 1991). Hence, earlier research has tried to use RBV to explain organizational decision-making as an independent organizational motivation. According to Braganza et al. (2017), who adopt an RBV viewpoint, organizational resources related to big data can be utilized to obtain a competitive edge.

The research concluded that big data analysis contributes to achieving the dimensions of organizational adaptability, as big data analysis contributes 10% (R^2 0.10) to achieving Creating Change, while it contributes 13% (R^2 0.13) to achieving Customer Focus, and the highest of them is organizational learning, where big data contributes to achieving organizational learning by 25% (R^2 0.25). The results corroborate the findings of earlier research on this influence. For instance, Tiwari et al. (2018); Mello & Martins (2019) claim that improving corporate reporting, particularly with regard to dynamic, real-time updates that boost accuracy, is the biggest advantage of leveraging big data. BDA analyzes a lot of data that changes quickly in this newly redesigned corporate reporting to provide stakeholders with timely information.

The conclusion that Big Data Analytics (BDA) has a greater impact on Organizational Learning ($R^2 = 0.256$) than Creating Change and Customer Focus is consistent with recent empirical research emphasizing the crucial role that data-driven capabilities play in knowledge production and learning processes. According to earlier studies, BDA promotes learning-oriented routines by improving an organization's absorptive capacity, or its capability to take in, analyze, and apply new information (Mikalef et al., 2020; Gupta & George, 2016). This outcome is especially likely in the context of Egypt's automotive industry, since many businesses are presently making investments in technical training and data infrastructure as part of larger digital transformation projects.

Compared to external customer-focused or change-creation techniques, which call for longer time horizons and more significant cultural adjustments, such in-

vestments typically have an earlier and more immediate impact on internal learning processes. The idea that data-driven capabilities first improve knowledge-based routines before translating into larger adaptive behaviors is supported by this pattern, which theoretically implies that BDA serves as a learning-enabling resource within the RBV framework (Wamba et al., 2017). Therefore, these results contribute to the body of literature by showing that BDA's most direct and significant effect in emerging markets is to build organizational learning systems, which in turn support higher-order adaptation outcomes.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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