"Adoption of big data analytics in medium-large supply chain firms in Saudi Arabia"

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BUSINESS PERSPECTIVES

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ADOPTION OF BIG DATA ANALYTICS IN MEDIUM-LARGE SUPPLY CHAIN FIRMS IN SAUDI ARABIA

Abstract

Big Data Analytics (BDA) is one of the most digital innovations for supporting supply chain firms' activities. Empirically, multiple benefits of BDA in Supply Chain Management (SCM) have been demonstrated. The study aimed to investigate the relationship between technical, organizational, and environmental factors and supply chain firms' performance using the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovation (DOI) theory. This study was conducted at medium-large supply chain firms in Saudi Arabia, the sample size reached 700 firms recognized by Saudi Arabia's Ministry of Commerce and Industry in different domains. In this study, a questionnaire was used to collect primary data. The collected data are analyzed using SPSS version 26.0. SPSS is used to describe respondents' demographic profiles. The percentage of respondents to the questionnaire reached 57%. In addition, to test hypotheses and accomplish research goals, PLS-SEM version 3.0 is used to examine the relationship between independent and dependent variables. From the PLS results, the study reported that complexity (β = 0.097, t = 2.817), security (β = 0.222, t = 3.486), IT expertise (β = 0.108, t = 1.993), and external support (β = 0.211, t = 3.468) were positively related to firm's performance; in contrast, relative advantage (β = –0.006, t = 0.200), compatibility (β = –0.020, t = 0.314), top management support (β = –0.046, t = 0.386), organizational resources (β = –0.065, t = 1.179), competitive pressure (β = –0.011, t = 0.199), and privacy (β = –0.05, t = 0.872) were negatively related to firm's performance.

Keywords	supply chain management, performance, diffusion of innovation, technology-organization-environment, Saudi Arabia

INTRODUCTION

Saudi Arabia has established goals for 2020 and a strategic vision for 2030, focusing on logistics and supply chain management. One of the primary goals of these strategies is to diversify the country's economic streams away from oil. In Saudi Arabia, BDA technologies will be one of the primary facilitators for the success of Vision 2030, since data will power the Kingdom's blueprint for the future, creating new opportunities, expanding the economy, and transforming society, which are key objectives of the Saudi Vision 2030. Another goal is to increase investments and lead the digital economy through technology. The Saudi government is also looking for private-sector collaborations to develop information technology infrastructure and telecommunications (Thamir et al., 2020). Implementation of BDA may be problematic due to the high cost, liabilities, complexities, and applicability associated with new technological innovation. These factors might contribute to ambiguity in the choice to implement BDA in SCM operations.

Saudi Arabia, continuously shifting environmental patterns, mostly as a result of the Kingdom's Vision 2030 implementation and other un-

expected situations like as the COVID-19 epidemic, may cause Saudi firms to re-evaluate their choices, potentially leading them to adopt BDA in order to sustain, or indeed obtain, a market leader (Thamir et al., 2020). Additionally, big data helps firms improve their supplier evaluations and govern procurement activities in any circumstance. Firms may also simulate their supply networks using big data. While numerous studies have exhibited the advantages of utilizing BDA in SCM, research in developing economies is limited. Most of the previous research focused on rich industrialized countries. In contrast, few prior published studies have evaluated Saudi Arabia's drive to adopt and apply big data analytics technology to SC firms (Thamir et al., 2020). Furthermore, Choi et al. (2018) indicate increasing uses of BD technologies and strategies in many areas of SCM, such as prediction, income management, and risk assessment. However, many CEOs still do not use big data analytics in their decision-making activities.

The expected sample size reaches near 700 firms recognized by the Ministry of Commerce and Industry in Saudi Arabia in different domains. Therefore, the findings of this study will provide generalization knowledge and determine the main factors facing firms to adopt big data through testing the adoption of a big data model in firms. Furthermore, this study is important as it contributes to expanding the literature on BDA and SCM by conducting in Saudi Arabia. Moreover, it might used as a reference for future academics seeking to expand their study focus on factors affecting the adoption of big data technologies in middle east countries.

1. LITERATURE REVIEW

A supply chain is a network of suppliers, manufacturers, transportation companies, warehouses, retailers, and customers. Supply chain management aims to control the movement of finances, information, and goods within a supply chain in order to maintain a high degree of product availability and service to the customer at the lowest feasible cost. Nowadays, there is a plethora of records generated as a result of transactions between suppliers and purchasers. The use of big data methods and tactics in a variety of supply chain management themes, including forecasting, revenue management, and risk analysis, using case studies from leading brands. However, despite the rising use of big data in supply chain management, some managers continue to avoid incorporating big data analytics into their decision-making processes.

1.1. Big Data analytics adoption

The term "big data" refers to a massive dataset that cannot be controlled or analyzed using standard databases (Lin et al., 2019; Mishra et al., 2017). In comparison, other experts saw big data as a business strategy that enables organizations to examine merely a massive volume of data (Wright et al., 2019; Malaka & Brown, 2015). In addition, BDA is a holistic strategy for managing, processing and analyzing data of various sizes of (volume, variety, velocity, veracity, and value) required to provide actionable information for sustained delivery, performance assessment, and competitive advantage (Emani et al, 2015).

Generally, big data adoption has an impact on SCM performance in many aspects, and it is shown in many studies such as Thamir et al. (2020), Govindan et al. (2020), Verhoef et al. (2019), Kamble and Gunasekaran (2019), Feki (2019), Agrawal et al. (2015), and many more. However, Mikalef et al. (2019) observed that recent research asserted that a sizable proportion of firms are incapable of leveraging value from the prospects that BDA may provide for their businesses. Some academics have even rejected those businesses may improve their performance through BDA. As a result, there may be a lack of knowledge and conflicting opinions regarding how firms might profit from BDA funds (Wamba et al., 2017). Additionally, the promises of BDA are not thoroughly investigated by businesses such as SCM companies (Mikalef et al., 2019).

BDA's applications have contributed to the improvement and development of various business models, including Supply Chain Management (SCM) (Kamble & Gunasekaran, 2019; and Chehbi-Gamoura et al., 2020). Countless prior studies and publications had shown BDA adoption benefits, including improved risk reduction, demand forecasting, batch size optimization, in-

ventory reduction, and the development of more innovative solutions to boost the satisfaction of clients (Queiroz & Pereira, 2019; Tahiduzzaman et al., 2017; Galea-Pace, 2020; Nguyen et al., 2018; and Nambisan et al., 2019). Despite these benefits, other researchers claim that many organizations are hesitant to accept and use BDA technology (Arunachalam et al., 2018), necessitating an empirical investigation to ascertain the variables that impact and modify enterprises' motivation to adopt and use BDA in SCM.

1.2. Big Data analytics and supply chain performance

Many companies in various industries use big data analytics technology to manage risks, reduce operating costs, and improve supply chain visibility and traceability, Feki (2019). According to Queiroz and Pereira (2019), BD is a powerful tool to help organizations conduct analyses. According to Abawajy (2015), availability of large amounts of data may play an essential role in creating insights into decision-making processes. Zhu et al. (2018) believe that big data technology improves the performance of supply chain companies. Several previous studies conducted on the applications of big data analytics technology showed the possibility of applying the technology in various sectors (Grover & Kar, 2017; Palanisamy & Thirunavukarasu, 2017; Raut et al., 2019). Despite the hype around the adoption of big data, none of the studies has been investigated in-depth, particularly in a medium-sized enterprise. However, the relationship between the most emphasized factors for Big Data adoption evaluated in a specific situation, Baig et al. (2019) recommended using large samples and focusing on mixed-method methods. To develop and validate current theoretical models and ensure accuracy for future studies, an in-depth and detailed study is needed.

Supply chain analytics is not a new notion. Historically, supply chain management has depended on statistics and operations research to optimize supply and demand matching objectives. With the support of an information system, business analytics has a strong association with supply chain performance. Nevertheless, the emergence of big data applications in supply chain management does open up new possibilities. Supply chain

analytics is a generic phrase that is a term that refers to advanced big data analytics used in managing the supply chain. These analyses might be classified as predictive, descriptive, or prescriptive (Wang et al., 2016). Numerous benefits of BDA in SCM are supported by empirical research, including cost reductions, enhanced SC flexibility, and satisfied customers (Ramanathan et al., 2017). As a result, there is growing interest in defining a distinct skill set for SCM data scientists (Waller & Fawcett, 2013). Big data analytics is rapidly gaining traction among academics and is becoming a priority for businesses to deploy. Daily, incomprehensible amounts of data are transported and collected as a result of the widespread use and growth of big data-enabling tools such as social networks, mobile devices and identification technologies that give consent to the 'Internet of Things.' Given that increased data equates to increased knowledge, firms are increasingly leveraging these technologies to establish and preserve competitive advantage (Wamba et al., 2017).

1.3. Underpinning theory

A theoretical model is a collection of pre-existing, approved hypotheses taken from the academic literature. The TOE (technology organization environment) framework (Tornatzky et al., 1990) employed as the study's main underpinning theory and Diffusion of innovations (DOI) (Rogers, 1995) are some of the most often used Information systems (IS) adoption theories for analyzing individual or organizational IT adoption decisions. Many scholars have confirmed and tested these hypotheses in various adoption situations, including e-commerce, e-learning, healthcare, and tourism (Yadegaridehkordi et al., 2018; Chandra & Kumar, 2018; Fan et al., 2018). They play an important role in considering the aspects that affect any technology acceptance decision by generating a blueprint (Oliveira & Martins, 2011); theoretical models must be considered to solve big data acceptance and execution issues at the organizational or individual level. Several factors influence big data adoption, including IT infrastructure, usefulness, and complexity.

In conclusion, a survey of the literature, adopting big data analytics is the process through which an innovation changes the architecture of an organization. Big data adoption includes improved in-

formation processing methods and technological advancements that support decision-making. It gives organizations new opportunities to use information and gain a competitive advantage. The use of big data enhances risk prediction, boosts production, and efficiently satisfies customers. In addition, big data usage helps businesses and sectors to outperform their rivals. Therefore, big data use could be time-consuming and expensive, but the long-term advantages might lead to success.

While big data have been frequently employed in predictive research, there are relatively few studies measuring prediction error in large data. More exactly, beyond the raw data's quality, the accuracy of big data analysis is strongly influenced by the model used to analyses the data. We still have a long way to go in terms of generating metrics that can be used to assess the accuracy of a method for analyzing large data. The majority of current research on big data applications in supply chain management is theoretical and conceptual, with a distinct dearth of research on analytical models. Additionally, present analytical models focus primarily on the use of big data in modelling sustainability. As a result, there is still a gap in the use of big data to supply chain optimization. Even though empirical research has examined factors influencing BD adoption in a variety of areas, the prior literature demonstrates a dearth of empirical evidence for big data adaptation in Saudi Arabia. As a result, this study will focus on medium-large supply chain enterprises in Saudi Arabia in order to address this absence from the literature

2. AIMS AND HYPOTHESES

This study aims to examine the relationship between technical, organizational, and environmental factors, and SCM performance at medium-large supply chain firms in Saudi Arabia

Ten (10) hypotheses were formulated as follows:

H1:   *Relative advantage is positively related to supply chain management performance at Saudi firms.*

H2:   *Complexity is positively related to supply chain management performance at Saudi firms.*

H3:   *Compatibility is positively related to supply chain management performance at Saudi firms.*

H4:   *Security is positively related to supply chain management performance at Saudi firms.*

H5:   *Top Management Support is positively related to supply chain management performance at Saudi firms.*

H6:   *IT expertise is positively related to supply chain management performance at Saudi firms.*

H7:   *Organizational resources are positively related to supply chain management performance at Saudi firms.*

H8:   *Competitive pressure is positively related to supply chain management performance at Saudi firms.*

H9:   *External support is positively related to supply chain management performance at Saudi firms.*

H10: *Privacy is positively related to supply chain management performance at Saudi firms.*

3. METHOD

This study was conducted at medium-large supply chain firms in Saudi Arabia, the sample size reached to 700 firms recognized by Saudi Arabia's Ministry of Commerce and Industry in different domains (such as Airlines, Banks, Broadcasting & entertainment, Building materials & fixtures, Business support services, Exploration & Production, Food products, Food retailers & wholesalers, General mining, Heavy construction, Insurance, Investment Services, Marine transportation, Publishing, Railroad, Real estate holding & development, Restaurants, Specialty chemicals, telecommunications) and different locations (such as Riyadh, Dammam, Dhahran, Jeddah, Jubail, Khobar). The study was targeted employees at various levels within their organizations, including owners, senior management, middle management, information tech-

nology expertise, and staff members. The study sample also included all departments at supply chain firms such as procurement, inventory, buying, expediting, import/export, operations, and logistics. The study population was compiled from two primary sources. A commercial directory published by Saudi Arabia's Ministry of Commerce and Industry is the first source. The second source population for the study was derived from a Saudi Arabian commercial directory (Daleeli), which provided firm names, phone numbers, fax numbers, and web page links to broaden the target population.

To achieve the study's objectives, a quantitative methodology was employed. In this study, a questionnaire was used to collect primary data, the respondents were asked to answer the items presented in a questionnaire. The researchers conducted both online and hard-copy forms to distribute these questionnaires to the respondents within three months in the central cities of Saudi Arabia. The survey identified the demographic profile and included five variables, current position of employees, company field, company size by annual revenue, company size by employees, and company experience in the field of business. According to the survey's findings, the percentage of employees who responded to the questionnaire were workers in CIO/IT director/Technology director, and their percentage reached about 77.1%. In addition, most of the companies that responded to the questionnaire were companies working in the field of Transport/logistics/post, as their percentage reached 31.3%. Moreover, the percentage of responding companies in terms of annual revenues (85-150 million SAR) reached 52.1%. In the end, the responding companies met the employee size range (50-100 employees) (63.2%).

The questionnaire was divided into two sections, factors of adoption and firm performance. The Factors of Adoption consist of three main variables; Technical Contexts consist of four sub-variables (Relative advantage, Complexity, Compatibility, and Security). Organizational Contexts consist of three sub-variables (Top Management Support, IT expertise, and Organizational). Environmental context consists of three sub-variables (Competitive Pressure, External Support, and

Privacy). Measurement items of factors of adoption formation (37 question items) were adapted from Davis (1989), Boonsiritomachai (2014). The firm performance (Score) consists of five variables, which are Plan, Source, Make, Deliver, and Return. The measurement items for firm performance (17question items) were adapted from Santos and Leite (2018). The questionnaire's measuring items were all scored on a Likert scale with a range of 1 (Strongly Disagree) to 5 (Strongly Agree).

The pretest was done utilizing expert judgments, as the questionnaire in this study was composed of measurements from various situations. As a result, the questionnaire was revised based on the advice of three experts to assure the scales' reliability and validity. The expert's identity has been withheld to adhere to the expert's confidentiality obligations. a pilot test with 100 responders from one of the SCM firms included in this research is also done. All indicators have a Cronbach's Alpha value greater than 0.70. Technical Contexts $\alpha = 0.862$; Organizational Contexts $\alpha = 0.881$; Environmental Contexts $\alpha = 0.910$; And Firm Performance $\alpha = .915$) indicating adequate internal consistency.

The collected data is analyzed using Statistical Package of Social Science (SPSS) techniques via SPSS software version 26.0. SPSS is used to describe respondents' demographic profiles, report descriptive statistics, and Partial Least Squares Structural Equation Modelling (PLS-SEM) techniques via SmartPLS software version 3.0. PLS-SEM is applied to investigate the connection between independent and dependent variables to verify hypotheses and achieve research objectives.

4. RESULTS

The measurement model was assessed by evaluating outer loadings, composite reliability and validity, Cronbach's alpha (α), average variance extracted (AVE), and factor loadings, as shown in Table 1. All the constructs had Cronbach's alpha (α) and CR greater than 0.70, meeting construct reliability criteria. All average variance extracted (AVE) values were more significant than 0.50, meeting convergent validity criteria. And the factor loadings, greater than 0.70.

Table 1. Results of Outer Loading, Cronbach's Alpha, CR, and AVE for composite variables

Latent variables		Indicators	Factor loadings	Cronbach's alpha	CR	AVE
Technical Contexts	Relative advantage	TRA1	0.870	0.868	0.912	0.716
		TRA2	0.820			
		TRA3	0.856			
		TRA4	0.836			
	Complexity	TCOM1	0.779	0.762	0.848	0.583
		TCOM2	0.750			
		TCOM3	0.714			
		TCOM4	0.807			
	Compatibility	TCOP1	0.793	0.796	0.867	0.619
		TCOP2	0.796			
		TCOP3	0.813			
		TCOP4	0.743			
	Security	TSEC1	0.843	0.871	0.907	0.661
		TSEC2	0.767			
		TSEC3	0.850			
		TSEC4	0.736			
		TSEC5	0.861			
Organizational Contexts	Top Management Support	OTMS1	0.827	0.751	0.857	0.668
		OTMS2	0.778			
		OTMS3	0.845			
	IT expertise	OITE1	0.863	0.772	0.868	0.687
		OITE2	0.821			
		OITE3	0.803			
	Organizational Resources	OOR1	0.858	0.721	0.843	0.642
		OOR2	0.788			
		OOR3	0.755			
Environmental Contexts	Competitive Pressure	ECP1	0.859	0.843	0.895	0.68
		ECP2	0.793			
		ECP3	0.831			
		ECP4	0.813			
	External Support	EES1	0.857	0.787	0.876	0.702
		EES2	0.791			
		EES3	0.864			
	Privacy	EPR1	0.732	0.851	0.904	0.693
		EPR2	0.876			
		EPR3	0.835			
		EPR4	0.877			
Firm Performance	Plan	FPP1	0.848	0.726	0.845	0.647
		FPP2	0.842			
		FPP3	0.716			
	Source	FPS1	0.786	0.838	0.885	0.606
		FPS2	0.755			
		FPS3	0.831			
		FPS4	0.711			
		FPS5	0.805			
	Make	FPM1	0.825	0.848	0.892	0.624
		FPM2	0.791			
		FPM3	0.805			
		FPM4	0.704			
		FPM5	0.819			
	Delivery	FPD1	0.768	0.703	0.835	0.628
		FPD2	0.818			
		FPD3	0.789			
	Return	FPR1	0.723	0.832	0.888	0.666
		FPR2	0.860			
		FPR3	0.868			
		FPR4	0.804			

Note: Factor Loadings above 0.708; Cronbach's Alpha above 0.708; Composite Reliability (CR) above 0.708; Average Variance Extracted (AVE) above 0.50.

The structural model was assessed by evaluating collinearity statistics (VIF), coefficient of determination (R^2), path coefficients (β), effect size (f^2), and predictive relevance (Q^2). The VIF values were less than five, confirming collinearity. Furthermore, the path coefficients and total effects were analyzed and supported four out of ten hypotheses. The estimated model in this research study could explain 73.8% of the variance in the plan, 81.5% of the variance in source, 77.8% of the variance in the making, 67.7% of the variance in delivery, and 70.8% of the variance in return. Predictive relevance (Q^2) values were more outstanding than zero, indicating that the estimated model was predictive.

Table 1 shows the results, indicating that the importance of the path coefficient is proven using t statistics and p-value evaluation at the .05, .01, and .001 confidence interval levels.

Table 2 shows the structural model estimates of the hypothesized relationships, both direct and indirect effects. The direct effect of relative advantage on firm performance is statistically and negatively insignificant ($\beta = -0.006$, $p < 0.842$, $t = 0.200$), not supporting Hypothesis $H1$. The direct effect of complexity on firm performance is statistically significant ($\beta = 0.097$, $p < 0.005$, $t = 2.817$), supporting $H2$. The direct effect of compatibility on firm performance is statistically insignificant ($\beta = -0.020$, $p < 0.754$, $t = 0.314$), not supporting $H3$. Security directly affected firm performance that is statistically significant ($\beta = 0.222$, $p < 0.001$, $t = 3.486$), supporting $H4$. The direct effect of top management support on firm performance was statistically insignificant ($\beta = 0.046$, $p < 0.868$, $t = 0.386$), not supporting $H5$. The direct effect of IT expertise on firm performance is statistically significant ($\beta = 0.108$, $p < 0.047$, $t = 1.993$), supporting $H6$. Organizational resources on firm performance were statistically insignificant ($\beta = 0.065$, $p < 0.239$, $t = 1.179$), not supporting $H7$. The direct effect of competitive pressure on firm performance is statistically negative insignificant ($\beta = -0.011$, $p < 0.842$, $t = 0.199$), not supporting $H8$. The direct effect of external support on firm performance was statistically significant ($\beta = 0.211$, $p < 0.001$, $t = 3.468$), supporting $H9$. Finally, the direct effect of privacy on firm performance is statistically insignificant ($\beta = 0.05$, $p < 0.384$, $t = 0.872$), not supporting $H10$.

5. DISCUSSION

5.1. Discussion of the relationship between technical contexts and SCM performance

This section discusses how to evaluate hypotheses $H1$, $H2$, $H3$, and $H4$.

$H1$: Relative advantage is positively related to supply chain management performance at Saudi firms.

The data analysis results did not support $H1$, implying that there is no association between relative advantage and business performance. The study's findings on the link between relative advantage and business performance are less significant in the setting of Big Data adoption. Agrawal (2015) and Nam et al. (2015) found no evidence for relative advantage in studies of Big Data adoption, hinting that relative advantage may be redundant in such investigations. However, the lack of awareness of how big data analytics technology may be used to improve

Table 2. Path coefficient of variables

H	Paths	β	T statistics	P values	Support
H1	Relative advantage → Firm Performance	−0.006	0.200	0.842	No
H2	Complexity → Firm Performance	0.097	2.817	0.005	Yes
H3	Compatibility → Firm Performance	−0.020	0.314	0.754	No
H4	Security → Firm Performance	0.222	3.486	0.001	Yes
H5	Top Management Support → Firm Performance	0.046	0.868	0.386	No
H6	IT expertise → Firm Performance	0.108	1.993	0.047	Yes
H7	Organizational Resources → Firm Performance	0.065	1.179	0.239	No
H8	Competitive Pressure → Firm Performance	−0.011	0.199	0.842	No
H9	External Support → Firm Performance	0.211	3.468	0.001	Yes
H10	Privacy → Firm Performance	0.05	0.872	0.384	No

an organization's performance can negatively affect its adoption. In comparison to the first hypothesis. The employee of a business feels that big data analytics technology offers several benefits, including improving the firm's performance. As a result, the benefits of using big data analytics technologies are obvious to business decision-makers and staff.

H2: *Complexity is positively related to supply chain management performance at Saudi firms.*

The findings on the influence of complexity on business performance indicated a positive link, corroborating *H2*. This study suggested that the complexity of the firm had a positive correlation with its success. While earlier research indicates that complexity has a detrimental effect on BDA acceptance (Verma & Chaurasia, 2019; Agrawal, 2015), a few further studies indicate that complexity does not affect BDA (Lai et al., 2018) or other IT innovation adoption (Maduku et al., 2016). In comparison, the degree of complexity is mostly determined by the users who will interact with technology, as the descriptive demographics revealed that the majority of respondents (77.1 percent) specialize in information technology. As a result, users will have no difficulty interacting with this technology, since it is simple to grasp, engaging with it is clear and intelligible, and it is simple to become proficient at utilizing it.

H3: *Compatibility is positively related to supply chain management performance at Saudi firms.*

Analyses of the data indicate a negative correlation between compatibility and company performance. This means that the infrastructure compatibility for adopting big data analytics technology negatively affects the firm performance. Hence, *H3* is not supported. Previous studies have shown an insignificant effect of compatibility on BDA adoption (Maroufkhani et al., 2020). Furthermore, managers' decisions on BDA adoption are influenced by compatibility. Organizational decision-makers will be more receptive to adopting and using BDA technology in various aspects of supply chain operations if they believe it is consistent with the data acquired, current operating procedures, IT infrastructure, and company values and beliefs.

H4: *Security is positively related to supply chain management performance at Saudi firms.*

H4 is corroborated by the path coefficient values. As a result, the security factor and SCM performance have a favorable correlation. This result suggested that security was associated with company performance. In contrast, earlier research has established a negative correlation between security and the use of Big Data technologies (Salleh & Janczewski, 2016; Nguyen & Petersen, 2017). The survey resulted in a high mean security factor (4.40), indicating that businesses possess the necessary security capabilities to adopt this technology, possess the necessary skills to ensure data security when utilizing this BDA technology, can easily integrate security policies for technology, have adequate tools and mechanisms in place to ensure effective data protection when utilizing this BDA technology, and possess the necessary security capabilities to adopt this technology. As a consequence, businesses can protect their customers' data and prevent security concerns. The customers should have no concerns about security.

5.2. Discussion of correlation between organizational contexts and SCM performance

This section explains the methodology for evaluating hypotheses *H5*, *H6*, and *H7*.

H5: *Top management support is positively related to supply chain management performance at Saudi firms.*

The data analysis results did not support *H5*, indicating that there is a direct influence of top management support on business performance. This finding suggested that TMS had no bearing on company performance. On the other hand, the outcome contradicts earlier research indicating that TMS is a recurring and critical factor in organizations' intentions to utilize big data (Maroufkhani, et al., 2020; Thamir et al., 2020; Jang et al., 2018; Sun et al., 2019; Lai et al., 2018; Verma & Chaurasia, 2019; Nguyen and Petersen, 2017). However, senior management support is crucial in fostering a climate conducive to company adoption of new technologies (Asiaei & Rahim, 2019; Scupola, 2009; Maduku et al., 2016). Top ex-

ecutives are catalysts for organizational change, communicating and promoting values through a well-articulated vision for the business (Cruz-Jesus et al., 2019; Kandil et al., 2018). Furthermore, assistance from senior management can aid in the learning and spread of technology throughout the organization (Asiaei & Rahim, 2019). As a result, they are critical throughout the BDA adoption process. However, the study's findings indicate that this factor has a negligible effect on top management's adoption of big data technology, owing to the existence of other factors that may have a greater impact on technology adoption, such as security and privacy concerns, the technology uses, and IT expertise in big data analytics technology.

H6: *IT expertise is positively related to supply chain management performance at Saudi firms.*

The effect of IT expertise on firm performance revealed a positive relationship, therefore, supporting *H6*. On the other hand, these results implied that there is a positive relationship between IT expertise and firm performance. Therefore, empirical evidence indicates that IT competence has a beneficial effect on IT adoption across a range of technologies, including Big Data adoption (Nam et al., 2015). Expertise in information technology is regarded as one of the company's most valuable assets. Companies can provide all facilities to adopt big data analytics technology such as IT infrastructure, but they are facing big problems in providing big data technology specialists. Moreover, especially in the Middle East countries, the existence of IT expertise in BDA is very little, and it is not easy to attract them from other countries, so the presence of this expertise will greatly help the company's decisions in adopting big data technology to raise the performance of the company.

H7: *Organizational resources are positively related to supply chain management performance at Saudi firms.*

H7 is not supported based on the results of the path coefficient. As a result, the association between organizational resources and SCM performance is minimal. The findings corroborate prior studies (Alsaad et al., 2019; Wang & Ahmed,

2009; Thamir et al., 2020). Additionally, this study supports Gangwar (2018) finding that organizational resources may not have an impact on big data adoption at the original intention stage but rather only during the post-adoption phases, which reflects the degree of implementation and utilization. In addition, many firms seek to acquire benefits from using cloud computing technologies, where cloud computing can provide all the technical needs of firms, thus firms can save the costs of acquiring infrastructure and save time to manage it.

5.3. Discussion of correlation between environmental contexts and SCM performance

This section discusses hypotheses *H8*, *H9*, and *H10*.

H8: *Competitive pressure is positively related to supply chain management performance at Saudi firms.*

The data analysis results indicate that *H8* is incorrect, implying that there is a negative link between competitive pressure and company performance. By contrast, the findings contradict prior research on competitive pressure as a predictor of BDA uptake (Lai et al., 2018; Jang et al., 2018; Gangwar, 2018; Verma & Chaurasia, 2019; Schüll & Maslan, 2018; Thamir et al., 2020). Competitive pressure is a larger motivator when it comes to deciding to use Big Data technologies. This means that firms may feel obligated to adopt Big Data technologies ahead of time to prevent a future competitive disadvantage owing to competition pressure. As a result, if enterprises in Saudi Arabia wish to preserve their market position, the adoption of Big Data technology may be considered a strategic requirement.

H9: *External support is positively related to supply chain management performance at Saudi firms.*

The outcomes of the effect of external support on firm performance revealed a positive relationship, therefore, supporting *H9*. In other words, these results imply that there is a positive relationship between external support and firm performance. Furthermore, the research

finding consistent with previous research has provided a correlation between external support and new technology adoption (Al-Isma'ili et al., 2016; Premkumar & Roberts, 1999; Nguyen & Petersen, 2017; Hung et al., 2016). In light of the hypothesis's findings, the existence of vendors and agents in the Saudi market working to provide support and training for companies will motivate firms to adopt big data analytics technology, which will reflect positively on the firm's performance. As a result, the more external help available, the more probable it is that Big Data technologies will be embraced.

H10: *Privacy is positively related to supply chain management performance at Saudi firms.*

H10 is not supported based on the results of the path coefficient. Therefore, there is an insignificant relationship between privacy and SCM Performance. This finding suggested that security was related to the firm's performance. According to previous studies, the major concerns of business owners are when it comes to deploying data-related technologies, privacy

and security are paramount (Priyadarshinee et al., 2017). Fear of losing control of personal information and the danger of information being leaked to competitors may hinder BDA adoption. Additionally, Nam et al. (2015) uncovered evidence for a link between privacy regulations and Big Data usage in a prior study on the issue. Privacy issues are among the most important issues in Saudi society. Due to the nature of the conservative society, it is not easy to obtain all the information about customers because there is a belief among customers that it is possible to use this information for other things that go beyond marketing studies. In addition, there is a prevailing belief in the society of Saudi Arabia that their data is vulnerable to penetration or distortion or distribution to other parties. Despite the existence of regulations and legislation that punishes anyone who infringes the privacy of others with deterrent punishments, society still has a fear of sharing data with others. As a result, the presumed challenges associated with complying with privacy requirements decrease the likelihood that Big Data technologies will be implemented.

CONCLUSION

The purpose of this study was to investigate the relationship between technical, organizational, and environmental adoption factors, and SCM performance at medium-large supply chain firms in Saudi Arabia. Two crucial implications may be drawn from the PLS results. First, complexity, security, IT expertise, and external support factors demonstrate their positive effect on BDA adoption, which improves firm performance. In contrast, relative advantage, compatibility, top management support, organizational resources, competitive pressure, and privacy factors have been shown to negatively affect the adoption of BDA, thus decreasing firm performance.

Based on the findings, the study recommended that firms prioritize spreading and growing awareness inside the organization about the key advantages of BDA technology to all stakeholders. Additionally, firms must think about the challenges of implementing BDA technology as well as additional elements that might affect acceptance, such resistance to change, data quality and integration, organizational learning culture, and decision-making culture. Therefore, firms are required to develop appropriate plans on how to overcome these challenges during the planning stages for the deployment of technology.

Future studies should incorporate the suggested paradigm for big data analytics technology adoption with other theories, such as RBV, TTF, and TAM. The framework's ability to explain previously unrecognized features of big data analytics technology adoption and deployment may be enhanced by including more theory-based context. In the end, the study was limited to medium-sized Saudi Arabian supply chain companies. To generalize the study's results to the Saudi market, a framework that can be evaluated at small- to medium-sized businesses in Saudi Arabia would be needed.

AUTHOR CONTRIBUTIONS

Conceptualization: Adel Hamed, Abdul Manaf Bohari.
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