


# Study of the Environmental Factors' Effects on Big Data Analytics Adoption in Supply Chain Management

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## ABSTRACT

The current study combines the institutional theory and the TOE framework to examine the effects of environmental factors along with the mediating role of top managements support on the decision to adopt big data analytics (BDA) in supply chain management (SCM) in Saudi firms as context of a developing economy in transition. The statistical analyses of the PLSPM performed with Smartpls showed that the environment factors could affect directly and indirectly the intention to adopt BDA in SCM. From a theoretical perspective, combining TOE framework with an institutional theory perspective provided us with a research model that highlight the importance of TMS as a mediating factor that can help to assimilate the effects of environment factors when dealing with BDA adoption. From a managerial perspective, this research should be useful for practitioners involved in the SCM and interested by the use of BDA by showing them the critical roles that can be played by environment factors in the decision to adopt BDA in SCM.

## KEYWORDS

BDA, Competitive Pressure, SCM, Top Management Support, Trading Partner Readiness, Vendor Support

## 1. INTRODUCTION

One the most prominent information and communication technologies (ICTs) nowadays is big data (BD) and big data analytics (BDA), which refer to the processes and tools used in capturing, storing, distributing, analyzing, and gaining value from massive and diverse data sets obtained from internal and external sources (Gandomi & Haider, 2015, Gangwar, 2018). Firms have begun to see numerous opportunities by introducing BD strategies into their core business and operational functions to enhance the effectiveness of their decision processes and increase their customer satisfaction (Buganza et al., 2020). Firms are also leveraging BD to extend their capabilities into new contexts that exceeds the firm's boundaries such as supporting the entire supply chain and logistics management (Trabucchi & Buganza, 2019).

The adoption and use of big data analytics in supply chain management (SCM) has attracted the interest of both practitioners and academics (Lin, 2017; Nguyen et al., 2018; Yu et al., 2018).

DOI: 10.4018/IJEBR.309395

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According to Nurmilaakso (2007), the concept of SCM is related to the processes of planning, implementing, and controlling the bidirectional flow of information, products and money between the initial suppliers and final customers through different organizations. According to Feki et al., 2016, firms are adopting BDA in SCM in order to drive decisions and support actions linked to the flows and interactions among supply chain partners.

Simoes et al. (2019) assert that understanding how adoption decisions occur is very important for organizations to improve the outcome of their investments. However, they indicate that much of the current literature assumes that technology adoption is driven primarily by technological and organizational factors, despite the fact that the decision to adopt BDA may have more to do with the external environment in which an organization is located, than rational intraorganizational and technological criteria.

A few studies empirically examined BDA adoption in SCM within the context of developing countries. Moreover, the concepts of BDA and SCM are quite new to the managers within this context compared to the context of developed economies. Hence, top management decisions to adopt BDA in SCM in these firms could be more reliant on environmental factors such as the pressure intensity from competitors, the readiness levels of trading partners, and the degree of support from vendors.

To sum up, despite their crucial role on new technological innovations adoption, very limited research examined the effects of the environmental factors on big data adoption via top management support, particularly within the context of developing economies.

In order to improve our understating of these relationships, the current study combines the institutional theory and the TOE framework to examine the effects of the environmental factors along with the mediating role of top management support on the decision to adopt BDA in SCM in Saudi firms. The review of previous studies focusing on BDA adoption reveals three commonly used environmental factors (Competitive pressure, vendor support and Trading partners' readiness) in link with intentions. These factors are then considered in the current research.

## **2. LITERATURE REVIEW**

### **2.1 Environment Factors and Technological Innovations Adoption: A Theoretical Background**

#### ***2.1.1 The Institutional Theory Perspective***

Previous studies adopted different perspectives to identify the environment factors linked to technological innovations adoption (Teo et al., 2003; Liang et al., 2007; Gangwar et al., 2015; Lai et al., 2018; Smaoui Hachicha & Mezghani, 2018; Orji et al., 2020). One of the common theoretical perspectives used for this purpose is the institutional theory. This theoretical perspective highlights the role of external environmental factors in the adoption process of technological innovations, "arguing that institutional decisions are not only driven by organizational goals but also by other social factors" (Sun et al., 2018). Indeed, competitors, trading partners and vendors may put pressure on firms to adopt new technological innovations (Hossain & Qaaddus, 2010; Sun et al., 2018). These authors argue that a firm "might adopt a new innovation in order to follow its partners and maintain an internal balance with its trading partners" or in order to imitate the leading competitors and become homologous.

Based on the works of DiMaggio & Powell (1983), focusing on institutional isomorphism, Liang et al. (2007) assert that innovations assimilation is driven more by the need for organizational legitimacy "which eventually makes organizations more similar without necessarily making them more efficient, giving rise to institutional isomorphism". So, organizations undergo pressures to be isomorphic with their environment (Teo et al., 2003). Such pressures can be described as follows:

- **Coercive pressures:** Linked to “formal or informal pressures exerted on organizations by other organizations upon which they are dependent (DiMaggio & Powell, 1983)” as resource-dominant organizations (Teo et al., 2003).
- **Mimetic pressures:** Occur when an organization imitates the actions of other organizations perceived to be legitimate or successful in case of uncertainty, when technologies are poorly understood or when goals are ambiguous (Liang et al., 2007).
- **Normative pressures:** Linked to social contagions that occur when a focal organization is tied to other organizations that have already adopted an innovation (Teo et al., 2003). According to these authors, this creates shared norms between members of a network that influence the organizational behaviors. For a specific organization, “a greater extent of information system adoption by its suppliers and customers” would influence positively its intention to adopt the same systems (Zheng et al., 2013).

### 2.1.2 The TOE Framework

Another widely employed perspective for studying the environment factors in link with IT adoption is the TOE framework (Lin 2017). Besides organizational and technological contexts, the TOE also emphasizes the importance of the environmental context, which refers to the areas in which an organization conducts its business. The importance of the environmental context stems from its direct effect on organizational decision-making processes including the decision to adopt new technological innovations such as BDA (Gangwar 2018). TOE framework is marked by the integration of environmental factors to help fully understand the mechanism during the decision-making process linked to the IT innovation adoption (Lai et al., 2018).

Previous research (Alshamaila et al., 2012; Kwon et al., 2014; Gangwar et al., 2015; Alsaad et al., 2017, Gangwar 2018) investigated the impact of different external factors on the decision to adopt technologies. The literature review reveals that the commonly used environmental factors that have a more direct impact on IT innovations adoption are:

- **Competitive pressure:** It has been defined as a degree of outer pressure from competitors in same sector which lead usually to a set of changes and adapting new technologies (To & Ngai, 2006; Obal, 2017). Competitive pressure is considered as one of the most important environmental factors in information technology adoption (Kuan & Chau, 2001; Zhu et al., 2004) that explains the existing status of technology usage in the competitive environment (Chen et al., 2015). In link with IT innovations adoption, Petersen & Nguyen (2017) suggest that the competition's rules changes inducted by the competitors' adoption of IT innovations will push other firms to adopt these innovations in order to protect their competitive position.
- **Vendor support:** Besides being disruptive, the adoption of digital technologies is linked to many technical and organizational concerns. Thus, the vendors' support is considered as a key element when dealing with such technologies (Gangwar et al., 2015; Smaoui Hachicha & Mezghani, 2018). In their study on cloud computing adoption, Gangwar et al. (2015) argued that cloud providers support is a key factor due to the security concerns linked to data confidentiality. These authors suggest that the willingness to adopt the cloud-based solutions would be greater if firms expect regular support from cloud vendors in ensuring data availability and security.
- **Trading partners' readiness:** “Trading partners' readiness measures network externalities within the value chain” (Awa et al., 2016). The greater trading partner expertise provides firms with an external reason for innovation diffusion (Simatupang et al., 2002). When dealing with transactions along a supply chain, “there is need for integrated and electronically compatible trading systems that link the enterprises and their trading partners to provide internet-enabled services for one another” (Awa et al., 2016). Through their survey research on Enterprise Resource

Planning (ERP) systems adoption, these authors argue that trading partners' readiness influence significantly the adoption of IT innovations within the supply chain.

2.2 BDA Adoption in SCM

Huge volume of valuable data is generated every year within supply chains pushing involved firms to apply BDA “in their supply chain to reduce cycle time, react faster to changes, optimize performance and gain insight into the future” (Feki, 2019). Indeed, “organizations are immersed with data related to their SCM activities” (Alaskar et al., 2020). These data are collected from different sources, such as Web clicks, RFID, tags, sensors, loyalty cards, and barcodes (Al-Qirim et al., 2017; Zhong et al., 2016). Feki (2019) highlights the utility of BDA in managing risks, reducing costs, and improving supply chain visibility.

The benefits of BDA in managing the supply chain resources has attracted many academicians to investigate the adoption concerns linked to BDA. Alsadi et al. (2021) focused on the supply chain connectivity as a factor that can moderate the effects of organizational factors on BDA adoption. In a similar perspective, Lai et al. (2018) and Alaskar et al. (2020) integrated the moderating effect of environmental factors with a focus on both organizational and technological antecedents.

All of these studies confirmed the fact that BDA adoption in SCM needs to be considered from different perspectives since it involves technical and managerial challenges. However, one can note that the focus was mainly on the organizational resources and on the technology itself. The environmental issues were not considered deeply.

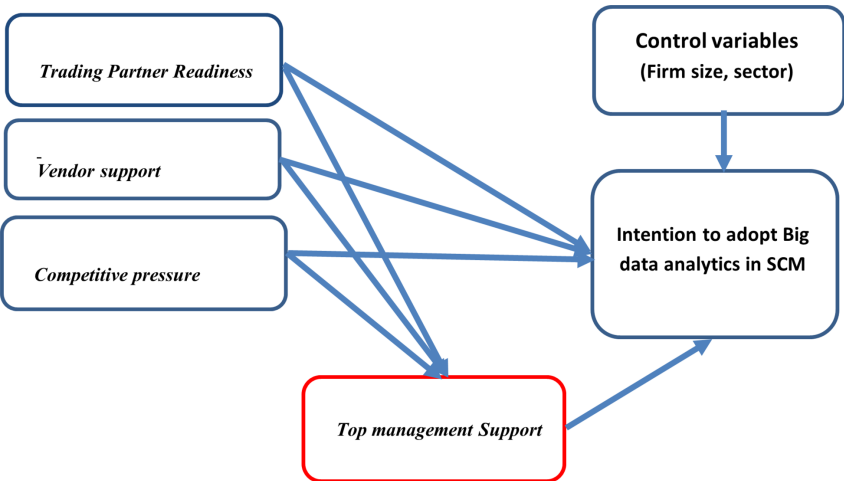
As discussed in the later sections and shown in Figure (1), the current study focuses on examining the effects of three environmental factors (Competitive pressure, vendor support and Trading partners' readiness), along with the mediating role of top management support.

3. ENVIRONMENT FACTORS AND BIG DATA ANALYTICS ADOPTION IN SUPPLY CHAIN MANAGEMENT: DEVELOPMENT OF A RESEARCH MODEL

3.1 The Effects of the Environment Factors on Intention to Adopt BDA

In order to highlight the direct effects of the environment factors on intention, the authors examined scholarly articles aiming to study IT innovations adoption at the firms' level. The TOE framework is largely adopted in such articles.

Figure 1. Research model



### 3.1.1 The Competitive Pressure

According to Porter & Millar (1985), the adoption of IT innovations by competitors may modify the industry structure, alter the rules of competition and create completely new value offerings and businesses. Then, firms would be pushed to adopt similar innovation to protect their competitive position (Petersen & Nguyen, 2017).

Verma & Chaurasia (2019) mentioned the importance of considering competitive pressure in BDA adoption. Indeed, they consider that, since the market competition is increasing, managers might feel the need to seek competitive advantages through BDA as suitable tools for a better understanding of customers and a more accurate data-driven decision making. Sun et al. (2019) argue further about the role of competition pressure to encourage firms to adopt BDA in order to get advantages that may help to get high level of market share.

Moreover, Chen et al. (2015) argue that while Liang et al. (2007) emphasis the role of competitive pressure to impact positively the top management support, the adoption of BDA by competitors will lead to changes in top management behavior to cope with market changes and reduce uncertainty of advanced technology.

Furthermore, the BDA adoption decision is usually based on the level of pressure received from competitors. Through a survey study, Lai et al. (2018) concluded that “when business competitors are widely using BDA, firms are urged to adopt BDA even complex as it might be” in order to keep up with the competition.

However, while studies show the positive impact of environmental pressure to start adoption of BDA, it will be negatively associated with the extent of BDA assimilation (Nam et al., 2019). Nevertheless, as many studies reinforced the impact of competitive pressure on the intention to adopt BDA (Gangwar, 2018; Chen et al., 2015; Agrawal, 2015; Petersen & Nguyen 2017; Jang et al., 2019; Schüll & Maslan 2018; Lai et al., 2018; Sun et al., 2019), we hypothesize:

**H1:** Competitive pressure is positively correlated to the intention to adopt BDA in SCM.

### 3.1.2 The Vendor Support

Firms need to establish good relationships with the vendors of new technologies in order to get the needed support during the early stages of BDA adoption. This is even more critical within the context of developing countries since firms in such context usually lack the needed internal technical expertise and skills and where new technologies are bought from foreign vendors who have limited presence in their countries (Duh & Fabiao, 2018).

The study of Ghosh (2018) measured different level of vendors support, starting from counseling and coordination, giving access to other user organization as case studies, answering questions about the technology, and providing dedicated project personnel to assist the adopting organization. His findings showed that vendor support strongly facilitates the adoption of cloud-based BDA in a sample of 30 medium-to-large-sized companies from variety of industries in the USA. Similarly, the findings of Gangwar (2018) showed that vendor support in the form of reinforcement, assistance, information sharing, and problem resolution also facilitates the adoption of big data in a sample of 478 companies from the manufacturing and service sector organizations in India. From a TOE perspective, Gangwar (2018) asserts that “support is required for proper technical design and problem resolution, responsive customization and solution completeness” leading to the fact that vendors can either encourage or discourage BDA adoption.

We therefore propose the next hypothesis:

**H2:** Vendor support has a positive influence on Big Data adoption in SCM.

### 3.1.3 The Trading Partner Readiness

Trading partners readiness (TPR hereafter) could be a critical factor for BDA adoption in SCM, since value can be maximized only when many trading partners along the supply chain are already using BDA or at least have made the decision to adopt this new technology. Previous research showed that a strong trading partner who has already adopted BDA tend to use its persuasive or coercive power to influence or pressure other trading partners to follow it (Iacovou et al., 1995). Gangwar & Date (2016) stipulate that “adoption of same technology amongst the business partners facilitates fully utilizing the innovation at an inter-organizational level” enabling firms to effectively respond to customer needs and market demands.

Evidence from existing research show that the effects of TPR on the adoption of new technological innovations are mostly positive. The majority of these papers examined its effect on EDI (Iacovou et al., 1995), ERP software (Awa et al., 2016), E-procurement (Soares-Aguiar & Palma-dos-Reis, 2008), E-commerce (Rozag et al., 2016) and E-business (Lai et al., 2007; Lin & Lin, 2008; Oliveira & Martins, 2010; Zhu et al., 2003). Most of the existing research examined the effect of TPR on technological innovations adoption such as E-business and ERP. As far as we know, only the study of Sun et al. (2019) investigated TPR effect on BDA adoption in a sample of 197 Chinese firms, and its findings showed that its effect was not statistically significant. Based on the previous discussion, we conclude that the question about the TPR effect on BDA adoption is still unanswered. This study will help to fill this gap by enhancing our knowledge regarding this effect within the context of a developing country (Saudi Arabia), thus we propose the following hypothesis:

**H3:** Trading partner readiness has a positive influence on Big Data adoption in SCM.

### 3.2 The Mediating Role of Top Management Support

TMS refers to the degree of support and commitment by senior management toward technological innovations (Jang et al., 2019; Salleh & Janczewski, 2016). It is widely and largely known that TMS is considered as a critical factor when dealing with IT adoption. According to Low et al. (2011), TMS is crucial “for creating a supportive climate and for providing adequate resources for the adoption of new technologies (Lin & Lee, 2005; Wang et al., 2010)”. With the increasing complexity of IT, “top management can provide a vision and commitment to create a positive environment for innovation (Lee & Kim, 2007; Pyke, 2009)” as these IT “may involve integration of resources and reengineering of processes” (Low et al., 2011).

In their study of ERP implementation, Mezghani & Mezghani (2014) found that TMS is directly and significantly linked to the ERP-business alignment as such support increases the mutual understanding between business managers and IT managers, leading to the successful implementation of ERP systems. Recently, more and more studies focusing on disruptive technologies’ adoption have highlighted the necessity of TMS to decide about such adoption. In their qualitative research aiming to understand cloud computing adoption, Smaoui Hachicha & Mezghani (2018) state that when top managers support innovation and create a favorable climate for it, the IT managers would be able to effectively assess the benefits and risks of cloud-based technologies. From the conducted interviews, many IT managers consider that “when top management support is low, perceived risks will be high and intention will be lowered”.

Similarly, several frameworks emphasized the role of TMS in building intentions to adopt technological innovations as Internet of Things (Hsu & Yeh, 2017), blockchain technologies (Orji et al., 2020) and social commerce (Abed, 2020).

Regarding BDA, Alaskar et al. (2020) affirm that “TMS support is considered as one of the main elements for success in BDA adoption as it delivers strategic direction, authority, resources, and a responsive environment during the adoption process (Sun et al., 2019)”. According to Maroufkhani et al. (2020), top managers are the key decision-makers who create “a supportive eco-system” to adopt

technological innovations, so their vision defines the level of support for BDA adoption. Thus, it is possible to propose the following hypothesis:

**H4:** Top management support is positively related to the intention to adopt BDA in SCM.

Besides encouraging the different initiatives within the organization, specifically linked to technological innovations, previous studies (as Liang et al., 2007; Zheng et al., 2013) recognized that top managers play an important role in assimilating a new IT system into an institutional environment. Liang et al. (2007) consider “that top management members are the primary human agency that translates external influences into managerial actions”. These authors assert that “top managers are not only influenced by others’ choices of IT products or services or of influential consultants”, they also try to benchmark their potential benefits which determine their actions regarding such products or services. Thus, the effects of environment factors on IT assimilation could be realized through the actions of top management that guide the organizational choices regarding the IT adoption (Liang et al., 2007).

Based on an institutional theory perspective, more studies have highlighted the role of top management as a mediator between environment factors and the decisions linked to IT adoption. Zheng et al. (2013) consider that top management commitment plays a significant mediating role between external pressures and intention to adopt e-government by transferring “external pressures into internal resource allocation and innovation adoption”. Similarly, the survey conducted by Gopalakrishna-Remani et al. (2019) suggest that top management participation and beliefs could mediate the effects of several external pressures on the level of IT adoption. Therefore, we hypothesize the following:

**H5:** Top management support mediates the effect of competitive pressure on intention to adopt BDA in SCM.

**H6:** Top management support mediates the effect of vendor support on intention to adopt BDA in SCM.

**H7:** Top management support mediates the effect of trading partner readiness on intention to adopt BDA in SCM.

#### 4. RESEARCH METHODOLOGY

Within environmental constructs and the intention to adopt BDA construct, the instruments available in the literature were used to develop the survey questionnaire (see Appendix). Then, a pilot study was carried out to test the suitability of the research instruments by distributing the survey to big data academics and professionals. The survey was built in two main sections: 1) demographics – industry sector, size of the firm, and respondents’ position; 2) extent of environmental indicators, top management support, and the intention to adopt BDA indicators – a six-point Likert scale was used, going from ‘strongly agree’ to ‘not at all agree’. The questionnaire was delivered to a total of 320 IS managers who belong to Saudi firms that use computerized SCM systems and who agreed to participate. According to Kearns & Sabherwal (2007), the IS managers are the “key informants” for surveys conducted in IT fields.

It was not possible to identify the population of firms to be studied since no official statistics were found about the use of computerized SCM systems within Saudi firms. Thus, a snowball sampling was performed. Such technique is suitable for sampling from hidden or hard-to-reach populations (Heckathorn, 2011).

Finally, we were able to gather 224 responses from which we removed four survey forms as there is missing data related to the main variables. Table 1 illustrates the main characteristics of the sample.

In the context of big data, previous studies (Chen et al., 2015; Dubey et al., 2019; Talwar et al., 2021) have used company size and industrial sector as main control factors. Company size as a control factor has been added because larger companies may have more capabilities than smaller companies,

**Table 1. Characteristics of the sample**

Respondents	Percentage
Respondents' position	
Chief information officer (CIO)	5.0%
System analyst	20.5%
IT manager	23.6%
Others (IT departments)	50.9%
Firm's size (number of employees)	
Less than 10	6.4%
Between 10 and 50	11.4%
Between 50 and 250	24.1%
More than 250	58.2%
Sector	
Manufacturing	8.2%
Telecommunication	16.4%
Trading	11.4%
Healthcare	5.0%
Banking	8.2%
Education	5.5%
Services	19.1%
Others	26.4%

as mentioned by Tippins & Sohi (2003). While industry sector type has been included since it can represent a variety of environmental aspects (Ashrafi et al., 2019).

In order to evaluate the proposed model and to test the relationships among constructs, the PLS-SEM (Partial Least Squares-Structural Equation Modeling) technique was used with the Smart-PLS software Version 3.3.3. The measurement model test was performed to address the relationships between indicators and their constructs, while the structural model test was used to address the relationships between constructs (Alexandre et al., 2010).

## 5. FINDINGS

### 5.1 Findings of Descriptive Analyses

After deleting one item (competitive1) as presenting a low factor loading, we obtained a satisfactory factor structure (table 2). The reliability tests were conducted through two steps. The first one was performed by checking Cronbach alpha values during factors analyses. The second one was done using PLSPM allowing to automatically calculate the composite reliability values during the structural analyses. In all cases, the obtained values were higher than 0.7 (table 2). This means “that the measures all consistently represent the same latent construct” (Hair et al., 2010).

To check the convergent and discriminant validity, the cross-loadings analysis (table 3) was followed by the examination of the Average Variance Extracted (AVE) values for each variable. As reported in table 4, all values exceed 0.5 which indicates a good convergence for all variables in



Table 2. Descriptive statistics

Constructs	Items	Loadings	AVE	CR	Cronbach's $\alpha$	rho_A
Competitive pressure	Competitive2	0.897	0.800	0.889	0.750	0.750
	Competitive3	0.892				
Intention BDA	Intent1	0.893	0.790	0.918	0.867	0.870
	Intent2	0.886				
	Intent3	0.887				
Trading partners readiness	Partners1	0.840	0.641	0.877	0.817	0.838
	Partners2	0.829				
	Partners3	0.768				
	Partners4	0.763				
Top management support	Top1	0.904	0.817	0.931	0.888	0.890
	Top2	0.915				
	Top3	0.893				
Vendor support	Vendor1	0.688	0.642	0.842	0.725	0.765
	Vendor2	0.867				
	Vendor3	0.837				

Table 3. Cross-loadings

	Intention BDA	Competitive pressure	Top management support	Trading partners readiness	Vendor support
Competitive2	0.306	<b>0.897</b>	0.201	0.352	0.405
Competitive3	0.312	<b>0.892</b>	0.173	0.319	0.301
Intent1	<b>0.893</b>	0.317	0.558	0.379	0.384
Intent2	<b>0.886</b>	0.336	0.476	0.357	0.328
Intent3	<b>0.887</b>	0.266	0.517	0.312	0.353
Partners1	0.392	0.332	0.363	<b>0.840</b>	0.512
Partners2	0.373	0.255	0.275	<b>0.829</b>	0.471
Partners3	0.260	0.341	0.292	<b>0.768</b>	0.358
Partners4	0.186	0.274	0.275	<b>0.763</b>	0.382
Top1	0.490	0.167	<b>0.904</b>	0.339	0.268
Top2	0.528	0.193	<b>0.915</b>	0.335	0.237
Top3	0.560	0.205	<b>0.893</b>	0.355	0.277
Vendor1	0.198	0.186	0.188	0.388	<b>0.688</b>
Vendor2	0.337	0.403	0.249	0.484	<b>0.867</b>
Vendor3	0.390	0.326	0.249	0.443	<b>0.837</b>

**Table 4. Validity tests (Fornell-Larcker Criterion)**

	Intention BDA	Competitive pressure	Top management support	Trading partners readiness	Vendor support	Mean Communalities (AVE)
Intention BDA	<b>0.889</b>					<b>0.790</b>
Competitive pressure	0.345	<b>0.894</b>				<b>0.800</b>
Top management support	0.583	0.209	<b>0.904</b>			<b>0.817</b>
Trading partners readiness	0.394	0.375	0.380	<b>0.801</b>		<b>0.641</b>
Vendor support	0.401	0.395	0.289	0.548	<b>0.801</b>	<b>0.642</b>

reference to Hair et al. (2010). The correlations between the main variables are also lower than the square root of the AVE of each variable.

Regarding the Heterotrait-Monotrait Ratio (HTMT) findings reported in table 5, all values are below the threshold of 0.9 suggested by Hair et al. (2019). Thus, discriminant validity is also demonstrated.

By performing a single-factor test, we obtained 68.78% as the total explained variance and 38.25% as the variance of the first factor from the unrotated factor solution. In reference to Podsakoff et al. (2003), such results suggest no common method bias in this study.

## 5.2 Findings of Explanatory Analyses

The analysis of the structural model performed with Smart-PLS brings the following findings (figure 2 and table 6) according to which the intention to adopt BDA in SCM is highly influenced by the identified variables ( $R^2 = 0.427$ ).

Besides  $R^2$ , the PLS path model's predictive accuracy is also assessed by calculating the  $Q^2$  (the blindfolding-based cross-validated redundancy measure) values. According to Hair et al. (2019), " $Q^2$  values should be larger than zero for a specific endogenous construct to indicate predictive accuracy of the structural model for that construct". In the current research, the  $Q^2$  values for the endogenous variables (Top management support and intention BDA) are, respectively, 0.117 and 0.317. Such values support the predictive relevance of the path model.

Among the identified environment factors, the analyses of path coefficients (table 6) reveal significant direct effects of both "vendor support" and "competitive pressure" on the intention to

**Table 5. Validity tests (Heterotrait-Monotrait Ratio (HTMT))**

	Intention BDA	Competitive pressure	Top management support	Trading partners readiness	Vendor support
Intention BDA					
Competitive pressure	0.428				
Top management support	0.661	0.255			
Trading partners readiness	0.446	0.478	0.439		
Vendor support	0.483	0.514	0.354	0.693	

Figure 2. The fitted model (SmartPLS version 3.3.3)

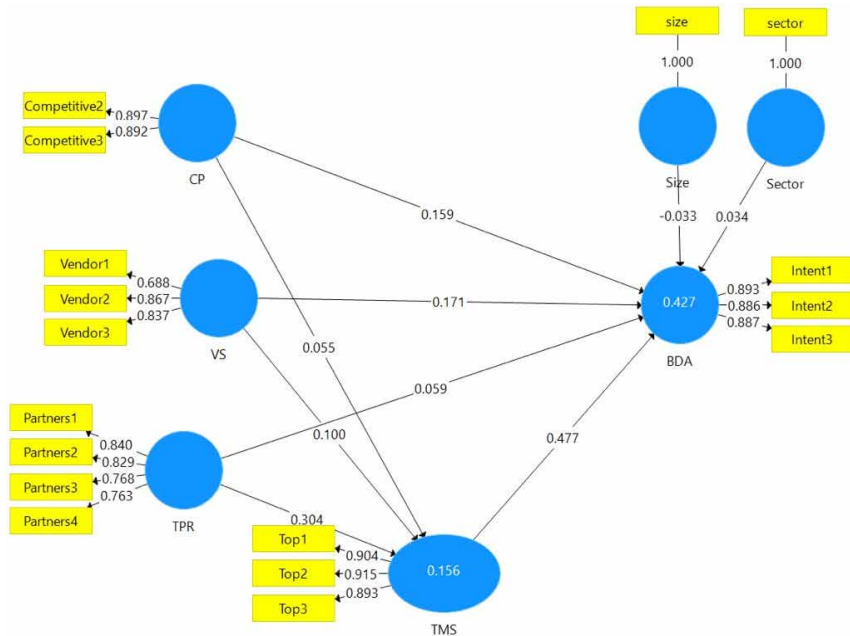


Table 6. The paths coefficients (Author calculated data)

Path		Value	(STDEV)	T Statistics	P Values	f <sup>2</sup>	Decision
Intention (R <sup>2</sup> = 0.427; STDEV = 0.059, P value = 0.000)							
CP → BDA (H1)		0.159	0.060	2.636	0.009	0.035	Supported
VS → BDA (H2)		0.171	0.089	1.921	0.055	0.033	Supported
TPR → BDA (H3)		0.059	0.066	0.898	0.370	0.004	Not supported
TMS → BDA (H4)		0.477	0.069	6.909	0.000	0.335	Supported
Control variables	Firm Size	-0.033	0.053	0.631	0.529	0.002	Not supported
	Sector	0.034	0.060	0.568	0.570	0.002	Not supported

adopt BDA, thus H1 and H2 are supported, while H3 is not supported since the impact of “trading partner readiness” is non-significant. Findings also show that TMS as an antecedent has a significant direct effect on BDA, thus H4 is supported.

In addition, the proposed control variables (industry sector and firm size) have no significant impact. As a result, we may conclude that developing big data capabilities can be helpful to the intention of big data adoption for all firms of all sizes and industries.

The current study also examined the indirect effects of the environment factors on BDA via TMS as a mediator of these effects. The f<sup>2</sup> (effect sizes) values reported in table 5 support the mediation effect of TMS. Hair et al. (2019) affirm that “values higher than 0.02, 0.15 and 0.35 depict small, medium and large f<sup>2</sup> effect sizes”. The effect size of TMS is about 0.335 which mean that the removal of this construct from the structural model has a high effect on the R<sup>2</sup> of BDA intention. This proves the existence of mediation effects (Mellouli et al., 2020).

Nevertheless, table 7 shows that only “trading partner readiness” is linked significantly to intention in an indirect way via TMS. In other words, TMS mediates positively and significantly the link between “trading partner readiness” and intention. Thus H7 is supported while H5 and H6 are not supported.

## 6. DISCUSSION

### 6.1 The Effects of the Environment Factors on Intention

The current study aimed to empirically test the direct effect of competitive pressure on the intention to adopt BDA in SCM. Our findings support such direct effect within the context of Saudi Arabia. The introduction of the 2030 vision has intensified competition for local firms in recent years. This vision aimed to modernize the economy and attract hundreds of international companies to the Kingdom (Al-Jadaan, 2021). This growing competitive pressure is perceived by Saudi firms as a major threat and could have urged them to defend their markets and improve their competitive position by introducing BDA innovation to their SCM operations. Such result is consistent with previous studies findings (Gangwar, 2018; Lai et al., 2018; Schüll & Maslan, 2018; Jang et al., 2019; Verma & Chaurasia, 2019).

The findings also showed that vendor support has a direct impact on the decision-making regarding BDA adoption in SCM within Saudi firms. Since BDA is a relatively new and complex technological innovation, most Saudi firms may lack the technical knowledge and expertise needed to adopt and implement BDA. This implies that these firms will be very reliant on dedicated vendors for continued coordination and services including counseling, training, planning, problem resolution, patches, and enhancements. These results are similar to the results of Alshamaila et al. (2013), Gangwar (2018) and Ghosh (2018).

Finally, these research findings show that trading partners’ readiness does not have a statistically significant direct effect on BDA adoption within Saudi firms. As mentioned in section (3.1.3), and to the best of our knowledge, only the study of Sun et al. (2019) examined the direct effect of TPR on BDA adoption. The results of the current study match and confirm their findings in this regard. However, as we show in the next section, this study improves our understanding of this relationship by taking into consideration the mediating role of TMS.

### 6.2 The Mediating Role of Top Management Support

The theoretical model of this study proposed TMS as antecedent and mediator of the environmental effects on BDA adoption. We examined the effect of TMS on BDA intention. The significant and strong link (0.477) found in this study confirms the fact that, as reported in Alaskar et al. (2020), TMS remains a crucial factor in making decisions regarding IT innovations adoption. When dealing with BDA adoption, TMS brings the strategic direction and the required resources in order to adopt BDA effectively, mainly in SCM (Sun et al., 2019; Alaskar et al., 2020). The results show that the respondents consider BDA adoption in SCM as a strategic issue that needs support from top management. In fact, the use of such IT in supply chains would affect “inter-organizational” processes that exceed the operational level of work and require particular attention from high level of management. Thus, the hypothesis H4 is supported.

Table 7. Indirect effects (Mediation results)

Path	Value	(STDEV)	T Statistics	P Values	decision
CP → TMS → BDA (H5)	0.026	0.042	0.623	0.534	not supported
VS → TMS → BDA (H6)	0.048	0.040	1.208	0.228	not supported
TPR → TMS → BDA (H7)	0.145	0.042	3.494	0.001	supported

Regarding the mediating effect of TMS between environment factors and intentions, the findings did not support all the theoretical background identified in the literature review. As mentioned above, TMS does not seem to mediate the links between “vendor support” and “competitive pressure”, on one hand, and intention to adopt BDA on the other hand (H5 and H6 not supported). Although previous studies (as Liang et al., 2007; Li & Wang, 2018) showed significant links between external pressures and TMS, Zheng et al. (2013) found in their survey that competitive pressure is not always an important impetus for top managers to make their decisions regarding IT adoption. In other words, these authors affirm that top managers are subject to pressure from their peers but do not automatically consider their pressure because they depend more on other institutional factors. Indeed, in their study, Zheng et al. (2013) found that top managers consider mainly their superior organizations when to deal with IT adoption because their work is closely linked to them.

Such situation may be reflected to the current study since TMS is statistically linked to “trading partner readiness”. In fact, the adoption of BDA in SCM would affect the interactions with trading partners as key participants in the supply chain. As a result, when deciding on IT innovation adoption and use within the supply chain, it is more prudent to consider mainly these partners. Such an idea can be also justified in reference to Lai et al. (2018) who assert that, in the context of supply chains, “it is reasonable that the higher connected the SC is, the more possible for suppliers to cooperate with each other; thus, top managers might be more optimistic to use BDA”.

Finally, the absence of indirect effect of “vendor support” through TMS confirms the fact that the degree of support provided by top managers for BDA adoption in SCM relies more on elements linked to the supply chain (such as exiting trading partners). Other elements (technological, competitive, etc.) affects rather the adoption concerns rather than what top managers would provide for such adoption.

## 7. CONCLUSION AND IMPLICATIONS

In the light of the increasing necessity of digital coordination and collaboration between trading partners in the current period of pandemic, the present research joins previous studies focusing on BDA adoption in the SCM. In order to highlight the influence of the current context on BDA adoption, the authors tried to identify the main environment factors that could affect the intention to adopt BDA in SCM.

Through a literature review, we developed a research model in which three environment factors (competitive pressure, vendor support and trading partners’ readiness) were examined as antecedents of intention. This choice was based on the TOE framework as a commonly used perspective when dealing with environment factors in link to IT innovations adoption.

While recent studies, as Lai et al. (2018) and Alaskar et al. (2020), focused mainly on the direct and moderation effects of environment factors, this study highlighted the indirect effects through TMS by combining the TOE framework with the institutional theory perspective. Indeed, a review of studies on IT adoption, with a focus on this theory, revealed that TMS should be considered to assimilate the environmental pressures in the decisions linked to IT adoption. In other words, combining TMS with the environment factors should provide a deeper understanding of the effects of such factors on IT adoption.

The statistical analyses performed with Smartpls showed that competitive pressure and vendor support influence directly the intention to adopt BDA in SCM. TMS did not seem to play a significant mediating role regarding the effects of these two factors on intention. This can be explained by the fact that top managers do not consider such factors when they develop their opinions regarding the BDA.

However, the findings showed a strong mediating effect of TMS when dealing with the TPR effect on intention to adopt BDA in SCM. As the focus is on SCM in particular, it is essential that top managers consider their partners in decisions linked to the adoption and use of IT innovations within the supply chain.

From a theoretical perspective, combining TOE framework with an institutional theory perspective provided us with a research model that highlights the importance of considering environment factors when dealing with BDA adoption in two ways: directly and through TMS. Thus, besides the moderating effects of environment factors already reported in previous studies, the findings of the current research support the fact that such factors can be considered as determinant and antecedents of intentions to adopt BDA in SCM. Also, although our findings did not support the mediating effect of TMS for all considered factors, the idea that TMS is essential to assimilate the effects of environment factors when dealing with BDA adoption remains valuable. The current study supports the fact that environment factors should be integrated and related to organizational factors to provide a deeper understanding of their effects. Also, when the use of the institutional theory is mainly linked to external pressures (from competitors or partners), the current study integrated also the vendors' support as a crucial environmental factor since vendors can inflict high pressure over firms by reinforcing them to adopt advanced technological innovations (such as BDA) due to their technical expertise and their ability to facilitate the adoption of big data by offering needed resources, skills and problem resolution.

From a managerial perspective, this research should be useful for practitioners involved in the SCM and interested by the use of BDA by showing them the critical roles that can be played by environment factors in the decision to adopt BDA in SCM. In addition to the firm's readiness in term of financial resources and skills, managers need to consider external factors to develop their opinions regarding BDA adoption. Moreover, as disruptive technologies, BDA tools need to be adopted carefully for a successful digitalization of the supply chain. This makes it crucial to assess BDA vendors and analyze the competition involvement in such technologies.

One of the most important implications of the current study is the vital role of top management support in leveraging the effect of Trading partners readiness on the intention to adopt BDA in supply management. Firms, at the present time, can no longer compete at the individual entity level but as integral members of the supply chain (Green et al., 2006; Swee Lin Tan et al., 2014; Tseng & Liao, 2015). This fact also means that the intention to adopt BDA as a new technological innovation requires top management support to ensure the readiness of all trading partners for the adoption decision and, later, to effectively employ the adopted BDA technology in enhancing information sharing and collaborative activities among the multiple partner firms along the entire supply chains (Alsadi & Aloulou, 2021).

Consultants and managers should consider the importance of TMS once more when dealing with BDA adoption. Besides the direct effect on the adoption intention emphasized in several studies, the current research findings should push managers to consider TMS in other levels in order to better assimilate some external effects, mainly within the supply chain. As reported in this study, top managers are well positioned to assess the readiness of their partners before making any choice linked to the use of IT innovations in the supply chain. Indeed, in the post covid-19 pandemic era, the readiness of trading partners for the adoption of BDA to support SC activities is particularly important for firms within developing economies in transition similar to the Saudi context, since a growing number of multi-national firms are expected to shift their operations from China to developing countries in order to enhance the global supply chains resilience (Sajjad, 2021).

Beyond the contributions, it is important to address the main limitations of the current research. Indeed, not all environmental factors, nor other mediating factors are considered to study the intention to adopt BDA in SCM. Following a contingency perspective, other organizational factors should be considered in further research to provide more understanding about the effects of environment factors on intentions toward IT innovations. Supply chain-linked factors should also be integrated in order to get a deeper understanding of BDA adoption in SCM. Also, even if IS managers are considered as the key informants when dealing with IT adoption, it will be interesting to involve business managers in a similar survey as the identified factors are more related to the business context.

## REFERENCES

- Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. *International Journal of Information Management*, 53, 102118. doi:10.1016/j.ijinfomgt.2020.102118
- Agrawal, K. (2015). Investigating the determinants of Big Data Analytics (BDA) adoption in Asian emerging economies. *Proceedings of the Americas Conference on Information Systems (AMCIS)*.
- Al-Qirim, N., Tarhini, A., & Rouibah, K. (2017). Determinants of Big Data Adoption and Success. *Proceedings of the International Conference on Algorithms, Computing and Systems - ICACS '17*, 88–92. doi:10.1145/3127942.3127961
- Alaskar, T., Mezghani, K., & Alsadi, A. (2020). Examining the adoption of Big data analytics in supply chain management under competitive pressure: Evidence from Saudi Arabia. *Journal of Decision Systems*. Advance online publication. doi:10.1080/12460125.2020.1859714
- Alsadi, A. K., Alaskar, T. H., & Mezghani, K. (2021). Adoption of Big Data Analytics in Supply Chain Management: Combining Organizational Factors With Supply Chain Connectivity. *International Journal of Information Systems and Supply Chain Management*, 14(2), 88–107. doi:10.4018/IJISSCM.2021040105
- Alsadi, A. K., & Aloulou, W. J. (2021). Impacts of strategic orientations on Saudi firm performance: Is supply chain integration a missing link? *International Journal of Logistics Management*, 32(4), 1264–1289. doi:10.1108/IJLM-02-2020-0080
- Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England: A multi-perspective framework. *Journal of Enterprise Information Management*, 26(3), 250–275. doi:10.1108/17410391311325225
- Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management*, 47, 1–15. doi:10.1016/j.ijinfomgt.2018.12.005
- Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *The Journal of Supply Chain Management*, 50(3), 55–73. doi:10.1111/jscm.12050
- Buganza, T., Trabucchi, D., & Pellizzoni, E. (2020). Limitless personalisation: The role of Big Data in unveiling service opportunities. *Technology Analysis and Strategic Management*, 32(1), 58–70. doi:10.1080/09537325.2019.1634252
- Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, 32(4), 4–39. doi:10.1080/07421222.2015.1138364
- Christensen, C., & Raynor, M. (2013). *The innovator's solution: Creating and sustaining successful growth*. Harvard Business Review Press.
- Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897–904. doi:10.1016/j.jbusres.2015.07.001
- Fawcett, S. E., Osterhaus, P., Magnan, G. M., Brau, J. C., & McCarter, M. W. (2007). Information sharing and supply chain performance: The role of connectivity and willingness. *Supply Chain Management*, 12(5), 358–368. doi:10.1108/13598540710776935
- Fawcett, S. E., Wallin, C., Allred, C., Fawcett, A. M., & Magnan, G. M. (2011). Information technology as an enabler of supply chain collaboration: A dynamic-capabilities perspective. *The Journal of Supply Chain Management*, 47(1), 38–59. doi:10.1111/j.1745-493X.2010.03213.x
- Feki, M. (2019). Big Data Analytics Driven Supply Chain Transformation. In K. Mezghani & W. Aloulou (Eds.), *Business Transformations in the Era of Digitalization* (pp. 106–124). IGI Global. doi:10.4018/978-1-5225-7262-6.ch007
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137–144. doi:10.1016/j.ijinfomgt.2014.10.007

Gangwar, H. (2018). Understanding the Determinants of Big Data Adoption in India: An Analysis of the Manufacturing and Services Sectors. *Information Resources Management Journal*, 31(4), 1–22. doi:10.4018/IRMJ.2018100101

Gangwar, H., & Date, H. (2016). Understanding cloud computing adoption: A model comparison approach. *Human Systems Management*, 35(2), 93–114. doi:10.3233/HSM-150857

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, 28(1), 107–130. doi:10.1108/JEIM-08-2013-0065

Gebhart, M., Giessler, P., & Abeck, S. (2016). Challenges of the Digital Transformation in Software Engineering. *ICSEA, 2016*, 149.

Green, K. W. Jr, McGaughey, R., & Casey, K. M. (2006). Does supply chain management strategy mediate the association between market orientation and organizational performance? *Supply Chain Management*, 11(5), 407–414. doi:10.1108/13598540610682426

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308–317. doi:10.1016/j.jbusres.2016.08.004

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. doi:10.1108/EBR-11-2018-0203

Heckathorn, D. D. (2011). Comment: Snowball versus respondent-driven sampling. *Sociological Methodology*, 41(1), 355–366. doi:10.1111/j.1467-9531.2011.01244.x PMID:22228916

Hsu, C. W., & Yeh, C. C. (2017). Understanding the factors affecting the adoption of the Internet of Things. *Technology Analysis and Strategic Management*, 29(9), 1089–1102. doi:10.1080/09537325.2016.1269160

Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *Management Information Systems Quarterly*, 19(4), 465–485. doi:10.2307/249629

Jang, W., Soo-Sang, K., Sung-Won, J., & Gwang-Yong, G. (2019). A Study on the Factors Affecting Intention to Introduce Big Data from Smart Factory Perspective. In *Big Data, Cloud Computing, Data Science & Engineering* (Vol. 786). Cham: Springer International Publishing. doi:10.1007/978-3-319-96803-2\_11

Kearns, G. S., & Sabherwal, R. (2007). Strategic Alignment Between Business and Information Technology: A Knowledge-Based View of Behaviors, Outcome, and Consequences. *Journal of Management Information Systems*, 23(3), 129–162. doi:10.2753/MIS0742-1222230306

Khare, A., Stewart, B., & Schatz, R. (2017). *Phantom Ex Machina*. Springer International Publishing. doi:10.1007/978-3-319-44468-0

Kuan, K. K. Y., & Chau, P. Y. K. (2001). A perception-based model for EDI adoption in small businesses using a technology-organization-environment framework. *Information & Management*, 38(8), 507–521. doi:10.1016/S0378-7206(01)00073-8

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, 34(3), 387–394. doi:10.1016/j.jinfomgt.2014.02.002

Lai, F., Wang, J., Hsieh, C. T., & Chen, J. C. V. (2007). On network externalities, e-business adoption and information asymmetry. *Industrial Management & Data Systems*, 107(5), 728–746. doi:10.1108/02635570710750453

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *International Journal of Logistics Management*, 29(2), 676–703. doi:10.1108/IJLM-06-2017-0153

Lee, S., & Kim, K. J. (2007). Factors affecting the implementation success of Internet-based information systems. *Computers in Human Behavior*, 23(4), 1853–1880. doi:10.1016/j.chb.2005.12.001



- Li, L., & Wang, X. (2018). M-Commerce adoption in SMEs of China: The effect of institutional pressures and the mediating role of top management. *Journal of Electronic Commerce in Organizations*, 16(2), 48–63. doi:10.4018/JECO.2018040103
- Liang, Saraf, Hu, & Xue. (2007). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly*, 31(1), 59.
- Lin, C. (2017). *Exploring Big Data Capability: Drivers and Impact on Supply Chain Performance*. Academic Press.
- Lin, G. C., Wen, Z., Marsh, H. W., & Lin, H. S. (2010). Structural equation models of latent interactions: Clarification of orthogonalizing and double-mean-centering strategies. *Structural Equation Modeling*, 17(3), 374–391. doi:10.1080/10705511.2010.488999
- Lin, H. F., & Lee, G. G. (2005). Impact of organizational learning and knowledge management factors on e-business adoption. *Management Decision*, 43(2), 171–188. doi:10.1108/00251740510581902
- Lin, H. F., & Lin, S. M. (2008). Determinants of e-business diffusion: A test of the technology diffusion perspective. *Technovation*, 28(3), 135–145. doi:10.1016/j.technovation.2007.10.003
- Louati, R., & Mekadmi, S. (2019). Toward a Conceptualization of Big Data Value Chain: From Business Problems to Value Creation. In K. Mezghani & W. Aloulou (Eds.), *Business Transformations in the Era of Digitalization* (pp. 76–92). IGI Global. doi:10.4018/978-1-5225-7262-6.ch005
- Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems*, 111(7), 1006–1023. doi:10.1108/02635571111161262
- Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, 54, 102190. doi:10.1016/j.ijinfomgt.2020.102190
- Mellouli, M., Bouaziz, F., & Bentahar, O. (2020). E-government success assessment from a public value perspective. *International Review of Public Administration*, 25(3), 153–174. doi:10.1080/12294659.2020.1799517
- Mezghani, K. (2014). Switching toward Cloud ERP: A research model to explain intentions. *International Journal of Enterprise Information Systems*, 10(3), 48–64. doi:10.4018/ijeis.2014070104
- Mezghani, K., & Aloulou, W. (Eds.). (2019). *Business Transformations in the Era of Digitalization*. IGI Global. doi:10.4018/978-1-5225-7262-6
- Mezghani, K., & Mezghani, L. (2014). Effects of Business Managers' Skills on Enterprise Resources Planning Strategic Alignment. *American Journal of Business and Management*, 3(1), 15–20. doi:10.11634/216796061403518
- Nam, D., Lee, J., & Lee, H. (2019). Business analytics use in CRM: A Nomological net from IT competence to CRM performance. *International Journal of Information Management*, 45, 233–245. doi:10.1016/j.ijinfomgt.2018.01.005
- Nguyen, T., & Petersen, T. E. (2017). *Technology adoption in Norway: Organizational assimilation of big data* (Master's thesis).
- Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big Data Analytics in Supply Chain Management: A State-of-the-Art Literature Review. *Computers & Operations Research*, 98, 254–264. doi:10.1016/j.cor.2017.07.004
- Nurmilaakso, J.-M. (2008). Adoption of E-Business Functions and Migration from EDI-Based to XML-Based e-Business Frameworks in Supply Chain Integration. *International Journal of Production Economics*, 113(2), 721–733. doi:10.1016/j.ijpe.2007.11.001
- Obal, M. (2017). What drives post-adoption usage? Investigating the negative and positive antecedents of disruptive technology continuous adoption intentions. *Industrial Marketing Management*, 63, 42–52. doi:10.1016/j.indmarman.2017.01.003
- Oliveira, T., & Martins, M. F. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems*, 110(9), 1337–1354. doi:10.1108/02635571011087428

Orji, I. J., Kusi-Sarpong, S., Huang, S., & Vazquez-Brust, D. (2020). Evaluating the factors that influence blockchain adoption in the freight logistics industry. *Transportation Research Part E, Logistics and Transportation Review*, 141, 102025. doi:10.1016/j.tre.2020.102025

Petersen, T., & Nguyen, T. (2017). *Technology adoption in Norway: Organizational assimilation of big data*. Academic Press.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology*, 88(5), 879–903. doi:10.1037/0021-9010.88.5.879 PMID:14516251

Pyke, J. (2009). *Now is the time to take the cloud seriously*. White Paper. Available at: [www.cordys.com/cordyscms\\_sites/objects/bb1a0bd7f47b1c91ddf36ba7db88241d/time\\_to\\_take\\_the\\_cloud\\_seriously\\_online\\_1\\_.pdf](http://www.cordys.com/cordyscms_sites/objects/bb1a0bd7f47b1c91ddf36ba7db88241d/time_to_take_the_cloud_seriously_online_1_.pdf)

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Rozaq, M. K. A., Harsono, M., Wahyunengseh, R. D., Eliyana, A., & Suryani, D. Y. (2016). *Determinant of Intention of E-Commerce Adoption and Strategic Orientation as Moderating Variable In Family Business*. Academic Press.

Sabourin, V. (2019). 3D Printing as a Case of Disruptive Technology: Market Leverage and Strategic Risks for Traditional Manufacturing. In *Business Transformations in the Era of Digitalization* (pp. 1-19). IGI Global. doi:10.4018/978-1-5225-7262-6.ch001

Sajjad, A. (2021). The COVID-19 pandemic, social sustainability and global supply chain resilience: A review. *Corporate Governance*, 21(6), 1142–1154. doi:10.1108/CG-12-2020-0554

Salleh, K. A., & Janczewski, L. (2016). Adoption of Big Data Solutions: A study on its security determinants using Sec-TOE Framework. In *International Conference on Information Resources Management (CONF-IRM)*. Association for Information Systems AIS Electronic Library (AISeL).

Schüll, A., & Maslan, N. (2018). On the Adoption of Big Data Analytics: Interdependencies of Contextual Factors. *ICEIS*, (1), 425-431.

Skilton, M. (2016). *Building the digital enterprise: a guide to constructing monetization models using digital technologies*. Springer.

Smaoui Hachicha, Z., & Mezghani, K. (2018). Understanding Intentions to Switch Toward Cloud Computing at Firms' Level: A Multiple Case Study in Tunisia. *Journal of Global Information Management*, 26(1), 136–165. doi:10.4018/JGIM.2018010108

Soares-Aguiar, A., & Palma-dos-Reis, A. (2008). Why do firms adopt e-procurement systems? Using logistic regression to empirically test a conceptual model. *IEEE Transactions on Engineering Management*, 55(1), 120–133. doi:10.1109/TEM.2007.912806

Sonnenwald, D. H., Maglaughlin, K. L., & Whitton, M. C. (2001). Using innovation diffusion theory to guide collaboration technology evaluation. *IEEE 10th International Workshop on Enabling Technologies*.

Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems*, 58(3), 193–203. doi:10.1080/08874417.2016.1222891

Sun, S., Hall, D. J., & Cegielski, C. G. (2019). Organizational intention to adopt Big data in the B2B context: An integrated view. *Industrial Marketing Management*, 86, 109–121. doi:10.1016/j.indmarman.2019.09.003

Swee Lin Tan, C., Bi, R., & Smyrniotis, K. X. (2014). The role of market orientation in building supply chain capabilities for fast-growth family SMEs. *Small Enterprise Research*, 21(1), 14–32. doi:10.1080/13215906.2014.11082074

Talwar, S., Kaur, P., Fosso Wamba, S., & Dhir, A. (2021). Big Data in operations and supply chain management: A systematic literature review and future research agenda. *International Journal of Production Research*, 59(11), 1–26. doi:10.1080/00207543.2020.1868599

- Tenenhaus, M., Amato, S., & Esposito Vinzi, V. (2004). A global goodness-of-fit index for PLS structural equation modelling. In *Proceedings of the XLII SIS scientific meeting* (Vol. 1, pp. 739-742). CLEUP Padova.
- Teo, H. H., Wei, K. K., & Benbasat, I. (2003). Predicting intention to adopt interorganizational linkages: An institutional perspective. *Management Information Systems Quarterly*, 27(1), 19–49. doi:10.2307/30036518
- Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: Is organizational learning a missing link? *Strategic Management Journal*, 24(8), 745–761. doi:10.1002/smj.337
- To, M. L., & Ngai, E. W. (2006). Predicting the organisational adoption of B2Ce-commerce: An empirical study. *Industrial Management & Data Systems*, 106(8), 1133–1147. doi:10.1108/02635570610710791
- Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, 29(1), 28–45. doi:10.1109/TEM.1982.6447463
- Trabucchi, D., & Buganza, T. (2019). Data-driven innovation: Switching the perspective on Big Data. *European Journal of Innovation Management*, 22(1), 23–40. doi:10.1108/EJIM-01-2018-0017
- Tsai, M. C., Lee, W., & Wu, H. C. (2010). Determinants of RFID adoption intention: Evidence from Taiwanese retail chains. *Information & Management*, 47(5-6), 255–261. doi:10.1016/j.im.2010.05.001
- Tseng, P. H., & Liao, C. H. (2015). Supply chain integration, information technology, market orientation and firm performance in container shipping firms. *International Journal of Logistics Management*, 26(1), 82–106. doi:10.1108/IJLM-09-2012-0088
- Vassakis, K., Petrakis, E., & Kopanakis, I. (2018). Big data analytics: applications, prospects and challenges. In *Mobile Big Data* (pp. 3–20). Springer. doi:10.1007/978-3-319-67925-9\_1
- Verma, S., & Chaurasia, S. (2019). Understanding the Determinants of Big Data Analytics Adoption. *Information Resources Management Journal*, 32(3), 1–26. doi:10.4018/IRMJ.2019070101
- Vinzi, V. E., Trinchera, L., & Amato, S. (2010). PLS Path Modeling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement. In *Handbook of Partial Least Squares: Concepts, Methods and Applications*. Springer-Verlag. doi:10.1007/978-3-540-32827-8\_3
- Wang, Y. M., Wang, Y. S., & Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, 77(5), 803–815. doi:10.1016/j.techfore.2010.03.006
- Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *Management Information Systems Quarterly*, 33(1), 177–195. doi:10.2307/20650284
- Zheng, D., Chen, J., Huang, L., & Zhang, C. (2013). E-government adoption in public administration organizations: Integrating institutional theory perspective and resource-based view. *European Journal of Information Systems*, 22(2), 221–234. doi:10.1057/ejis.2012.28
- Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. *Computers & Industrial Engineering*, 101, 572–591. doi:10.1016/j.cie.2016.07.013
- Zhu, K., Kraemer, K., & Xu, S. (2003). Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*, 12(4), 251–268. doi:10.1057/palgrave.ejis.3000475
- Zhu, K., Kraemer, K. L., Xu, S., & Dedrick, J. (2004). Information technology payoff in E-business environments: An international perspective on value creation of E-business in the financial services industry. *Journal of Management Information Systems*, 21(1), 17–54. doi:10.1080/07421222.2004.11045797
- Zhu, S., Song, J., Hazen, B. T., Lee, K., & Cegielski, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. *International Journal of Physical Distribution & Logistics Management*, 48(1), 47–68. doi:10.1108/IJPDLM-11-2017-0341

## APPENDIX

Table 8. Questionnaire items

Variables	Items
Intention BDA (Lai et al., 2018)	Our firm intends to adopt big data analytics. Our firm intends to start using big data analytics regularly in the future. Our firm would highly recommend big data analytics for other firms to adopt.
Top management support (Maduku et al., 2016; Lai et al., 2018)	Top management would provide resources necessary for the adoption of big data analytics. Top management would provide necessary support for the adoption of big data analytics. Top management would support the use of big data analytics Top managers would be enthusiastic about adopting big data analytics.
Competitive Pressure (Maduku et al., 2016; Lai et al., 2018)	Our choice to adopt big data analytics would be strongly influenced by what competitors in the industry are doing. Our firm is under pressure from competitors to adopt to big data analytics. Our firm would adopt big data analytics in response to what competitors are doing.
Vendor support (Ghosh, 2018)	The big data tools vendor provides coordination and counseling to develop necessary strategies to plan tool adoption. The vendors provide access to other user organizations as case studies that can be used as reference models and examples. The Vendors provide consulting support to answer questions about the technology and ease the shortage of skilled personnel.
Trading partners readiness (Sun et al., 2019)	Majority trading partners requested implementation of big data analytics. Majority trading partners recommended implementation of big data analytics. Trading partners are generally very knowledgeable regarding technical matters. Trading partners contain considerable technical expertise.

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