Do companies adopt big data as determinants of Sustainability: Evidence from manufacturing companies in Jordan

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Abstract

Information and communication technology make it easier for managers to gather customer data quickly and efficiently. However, managing, analyzing and utilizing the vast amount of data for sustainability decision are not easy. Therefore, this study aims to examine the readiness of manufacturing firms in adopting big data analytics in sustainable development. Moreover, this study employed the Partial Least Square Structural Equation Modelling (PLS-SEM) technique and analyzes the data collected from 172 respondents working in different organizations in Amman and Jordan. The results reveal that there is a significant relationship between top management support and competitive pressures and intentions to adopt big data analytics. However, the moderating influence of perceived risk on the relationship between intention and actual use of big data has not been proved. The study provides fresh findings on determinants of intention to adopt big data analytics, actual use and moderating role of perceived risk within the model to develop sustainability. Furthermore, the study has a number of theoretical and practical implications. Our main findings provide a deeper understanding of the enablers of BDA adoption through the development of a framework that includes direct and moderating constructs, as well as recommendations to practitioners on how to enhance BDA adoption based on eight BDA enablers.

Keywords: Big data analytics; intention to adopt BDA; Jordan; manufacturing companies; perceived risk; sustainability

1. Introduction

There have been a number of strategies used by companies to grow and gain a competitive edge. Most companies need to look at gaining a competitive advantage to be more adaptable, efficient, and inventive (Soon et al., 2016). Considering this competitive environment, companies are nevertheless compelled to implement different cutting-edge information technologies (IT) to

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better their company activities and performance (Faizi et al., 2017). Climate change, environmental degradation, social injustices, and economic instability are becoming more acute global sustainability challenges, which require disrupted technology and innovation beyond incremental approaches (Appolloni et al., 2022; D' Adamo et al., 2022; Ikram et al., 2021). To serve their consumers more effectively and competitively than their competitors, companies must have access to various information related to client demands, attitudes, and so on. Consumers' data can be used by companies to determine when to offer discounts and how to improve their brand's image by analyzing when their consumers use their goods. . Data on our activities is being generated at an exponential rate in today's world (Cabrera-Sánchez & Villarejo-Ramos, 2020).

Companies that can turn consumer's data into real-time information to gain a significant competitive edge (Sivarajah et al., 2017). Big data may be regarded as an innovative application for corporate organizations as a new kind of information technology (IT) (Mahesh et al., 2018). Many businesses are starting to think about how they might profit from big data (Hajiheydari et al., 2021; Qin, 2012). In the field of information technology, the phrase "big data analytics (BDA)" has become a buzzword (Arrigo et al., 2021; Zomaya & Sakr, 2017). The adaption of BDA gives a competitive advantage to companies over their competitors (Fugini et al., 2021; Müller et al., 2018). BDA is a set of tools and processes for gathering, storing, and analyzing data that helps the companies to perform business intelligence tasks (Faizi et al., 2017). Further, it explains how to uncover hidden patterns from a set of raw data to make better judgments, increase productivity, generate knowledge, and improve inventions (Maroufkhani et al., 2020).

The use of BDA allows companies to analyze huge volumes of data instantly and become leaders in their fields (McAfee et al., 2012). The primary sources of BDA comprises on the data clouding, social media, and more to provide insights that company workers may use to make decisions (Bai et al., 2021; Zomaya & Sakr, 2017). The several studies endorse that, when properly implemented, BDA may have a significant influence on lowering company expenses, generating business insights, and uncovering strategic data, ultimately improving the quality and efficacy of business decisions (McAfee et al., 2012; Zomaya & Sakr, 2017).A growing number of businesses are implementing BDA as a result of its relevance. Given the advantages of BDA, many big companies have already used it for a variety of objectives, including forecasting new market trends and perceiving the behaviour of consumer and seeking new ways of performance improvement (Hajiheydari et al., 2021; Mandal, 2018).Due to the numerous benefits it offers its users at the strategic, tactical, and operational levels, BDA has been gaining popularity around the world . The adaptability rate of BDA technology is not high as predicted (Paley, 2017). Prior studies have reported that the BDA adoption is a determinant of organizational success (Behl et al., 2019; Cabrera-Sánchez & Villarejo-Ramos, 2020; Mahesh et al., 2018; Soon et al., 2016), however, the actual use of BDA within the firm is scarce (Maroufkhani et al., 2022). Unlike others this study fills the gap in the literature to investigate how the adoption of BDA plays a vital role in organizational success. Furthermore, this study employed perceived risk as a moderator, giving it a new insight. According to Grover & Kar (2017), there is a lot of potential for studies to investigate BDA acceptance, applications, and tools since BDA offers different benefits to businesses such as increasing productivity and competition. Another research found a BDA talent shortage and a skills gap between labor market requirements and knowledge available in the current workforce, which might be viewed as an impediment for organizations planning to adopt BDA (Johnson et al., 2021). One study attempted to develop a model of the link between BDA and SSCM based on Toulmin's argumentation model; the model identified BDA factors, facets of SSCM, and SSCM (Mageto, 2021), but this model was not empirically tested. Furthermore, another study presented a comprehensive analysis for the BD applications across different segments in food SCM via systematic review; nevertheless, the model that emerged was on conceptual framework of data-driven food SCM (Margaritis et al., 2022). This revealed a need and indicated a future research direction that more studies should be conducted to empirically evaluate the influence of BDA enablers on the intention to adopt BDA in the manufacturing sector, as our study did. Thus, the purpose of this study to understand the determinants of big data adoption in manufacturing companies and see the actual use of BDA within the firm by the moderating impact of perceived risk.

The structure of paper is followed as: Section 1 presents the literature review and development of hypothesis. The SEM and data collections explained in section 3. Whereas the result and discission is presents in section 4. The last section of study presents the conclusion and limitation of study.

2. Literature Review

2.1 Contemporary view of BDA

The contemporary view of BDA adoption in industrial context is a game-changer catalyst to take the precise and timely decision for high organizational performance (Maroufkhani et al., 2020). BDA has the potential to transform the corporate landscape through a variety of technical disruptions and approaches, making it easier to obtain various forms of real-time data for decision-making (Zomaya & Sakr, 2017). Businesses are gaining a competitive advantage over their competitors by using BDA Prior study such as Mahesh et al. (2018) conducted research to identify the variables that influence the decision to implement big data technology (BDT) in the Sri Lankan financial services industry, as well as to explore the nature of the link between those determinants and the decision to use BDT. Moreover, interestingly they found a positive relationship of compatibility, relative advantage, technological resource competency, organizational size, absorptive capacity, competition intensity, and regulatory support with adoption decision. Conversely, complex environment and uncertain systems have a negative relationship. Maroufkhani et al. (2020) conducted a study on BDA adoption in Small Medium Enterprises (SMEs) and identified the drivers and outcomes of BDA, by using the RBV and TOE models to check the effects of BDA adoption on technological advancement, organizational performance. Moreover, the outcome of this study reported the different technological aspects of BDA adoption in SMEs sector. Whereas complexity, ambiguity, and insecurity have a detrimental impact, but trialability and observability had the opposite effect.

BDA adoption among SMEs was influenced by both top management support and organizational resources. Due to this, external support was the only environmental factor influencing SMEs' adoption of BDA, while the effects of competition and government regulation were not considered. According to Gangwar (2018), a recent study examined the factors that determine BDA in India, and found that relative advantage, compatibility, complexity, and top management support, as well as firm size, competitive pressure, vendor support, data management, and privacy concerns, are all key factors affecting BDA adoption. Shahbaz et al. (2019), conducted a study in health care industry of Pakistan to investigate the technology acceptance model's credentials, along with task-technology fit, significantly improved behavioural intentions by using BDA.

Many studies attempted to identify challenges to sustainable initiatives in the context of the value chain, revealing a gap in knowledge about how risk management systems relate to sustainability management systems, how both influence business performance, and addressing the need for enhancing flexibility at various levels in the enterprise. All of these issues point to how businesses might benefit from technology like BDA in their operations. Risk management is critical in uncertain times because it prevents businesses from responding rapidly and improperly, allowing them to become more flexible and resilient. The ability to respond effectively to critical circumstances will be increased through enhancing organizational flexibility and via adaptation to high-stress environments (Settembre-blundo et al., 2021). As a result, manufacturing firms should have enough network-based applications and flexible systems to adopt new technologies like BDA and respond to changing circumstances successfully (Settembre-blundo et al., 2021). Within risk management decision-making processes, there is a positive relationship between sustainability and resilience. Risk management, supply chain flexibility, and internal integration may all help firms improve their financial performance by reducing risk and increasing resilience (Dwivedi et al., 2021). Furthermore, external factors can put companies' BDA adoption at risk, limiting their flexibility in responding to future customer demands. For example, in the presence of an insufficient regulatory environment toward BDA, there is a strong risk of penalizing not only the current development of an area in manufacturing processes, but also its future development (Dwivedi et al., 2021). Moreover, BDA technology enables new ways to apply big data in the future, which is of great relevance in terms of risk reduction. For example, the firm may use process information to improve production flexibility through production component variation management, thus lowering production risk (Ryabchikov & Ryabchikova, 2022). This study addresses the identification of factors that enable businesses to have the intention to adopt BDA given the perceived risk that BDA should be cost effective (Delhi et al., 2015; Dwivedi et al., 2021; Paul, 2020; Ryabchikov & Ryabchikova, 2022; Settembre-blundo et al., 2021). Moreover, the study of Behl et al. (2019) looked at the factors that make BDA implementation easier in an e-commerce business. It depicted the enablers' relationship and the degree to which they were associated. Various studies has shown the factors that impact BDA adoption and business performance, but the actual use intention and the mediation effect of perceived risk between adoption intention and actual use intention have yet to be discovered. For example, Raut et al. (2019) examined the determinants of sustainable business performance using seven BDA adoption dimensions. This study differs from Raut et al. (2019) in that we attempted to measure factors influencing BDA intention to use through three categories: technological, organizational, and environmental, which includes eight constructs that have an effect on BDA intention to use, which differ slightly from the previously mentioned study. Furthermore, the influence of BDA intention was examined directly on BDA adoption, as well as the moderating effect of BDA perceived risk between BDA intention to use and actual BDA adoption.

Table 1. Summary of the past studies

Author(s)	Independent variable	Dependent variable	Mediator/ Moderator	Major Findings
(Hajiheydari et al., 2021)	BDA enablers	BDA prioritization and adoption		The purpose of the study is to gain a better knowledge of the enablers that facilitate BDA implementation in the banking and financial services sectors through the lens of interdependence and interrelationships.
(Maroufkhani et al., 2020)	Technological factors, organizational factors, environmental factors	Big data analytics adoption, financial performance, market performance		SMEs have a significant effect on their marketing and financial performance through the adoption of BDA.BDA implementation can be successful if managers understand the factors that influence acceptance.
(Verma & Chaurasia, 2019)	Relative advantage, compatibility, top management support, organizational data environment	Big data analytics adoption		Relative advantage, complexity, compatibility, top management support, technology readiness, organizational data environment, and competitive pressure are significant determinants of DBA, whereas relative advantage, complexity, and competitive pressure are determinants of non-adopters.

(Sun et al., 2020)	Technology context, organizational context, environmental context	Technology innovation decision making		The empirical findings demonstrate that relative advantage, technological competency, technology resources, Organizational adoption of big data is heavily influenced by management support, competitive pressure, and regulatory environment. It helps to understand how big data dissemination works across industries with these findings.
(Gangwar, 2018)	Technology, organization, environment, security	Big data adoption		Relative advantage, compatibility, complexity, organizational scale, top management support, competitive pressure, vendor support, data management, and data privacy are all essential for both the manufacturing and service sector of India.
(Soon et al., 2016)	Perceived usefulness, perceived benefit, perceived analytics accuracy, perceived ease of use, perceived risk	Adoption of big data	Training	Research on technological acceptance and diffusion, as well as TAM and DOI integration, can provide the crucial foundation for researchers studying the adoption of big data-related activities by workers. Moreover, in conjunction with our findings, we will be able to conclude that Malaysian private companies are adopting big data effectively.
(Mahesh et al., 2018)	Technology, organization, environment	Adoption of big data technology		Compatibility, relative advantage, technological resource competency, organizational scale, absorptive capacity, competitive intensity, regulatory support, and organizational desire for big data technology adoption all show a strong positive relationship. But the complexity and environmental unpredictability, on the other hand, have a major negative impact on the same.
(Villarejo Ramos & Cabrera-Sánchez, 2019)	Performance expectancy, effort expectancy, social influence, facilitating conditions	Behavioural intention, usage behaviour	Resistance to use, perceived risk	The result shows the positive influence of the four factors on behavioural intention to use big data. The value of strong infrastructure outweighs the challenges that businesses experience in putting it in place. While organizations aiming to embrace big data anticipate positive outcomes, actual consumers are more cautious.
(Shahbaz et al., 2019)	perceived trust, perceived security, task technology fit, perceived ease to use, perceived usefulness	Behavioural intention to use BDA, actual use of BDA	Resistance to change	The technology acceptance model's credentials, along with task-technology fit, significantly improve behavioural intentions to use a big data analytics system in healthcare, eventually leading to actual usage.

2.2 Conceptual framework and hypothesis development

2.2.1 Influence of technological factors on BDA adoption intention

Adoption of a technology is determined by both its internal and external factors (Maroufkhani et al., 2020). BDA adoption is influenced by several technological factors, which impact the firm's decision to adopt it (Hajiheydari et al., 2021). As antecedents to any adoption decision, Rogers (1983) defined five technical characteristics: relative advantage, compatibility, complexity, trialability, and observability. However, Low et al. (2011) explicitly omitted the trialability and observability components and included the preceding three components. One of the factors is a relative advantage, in which the perceived benefit of new technology to specific organizational performance can have a significant impact on organizational adoption intentions (Gu et al., 2012).

The primary aspects of relative advantage in terms of organizational growth are typically regarded to be characteristics linked to value, competitiveness, and social standing (Sun et al., 2020; Thacker et al., 2022). The degree to which specific technology is seen as superior to the notion it succeeds is known as relative advantage, and it is an important element to consider when researching technology adoption behaviour (Mahesh et al., 2018). Therefore, the greater the apparent proportional benefit that big data may provide, the more motivated the company will be to adopt it. Moreover, technological factor that influences the BDA intention is ‘competence’. Kwon et al. (2014), reported a company's willingness to engage in BDA is influenced by its competence in preserving corporate data with quality. It will be easier to deploy BDA in a company if the installation of the BDA system requires similar technological infrastructure to the existing technology foundation (McAfee et al., 2012). The term "technological resource competency" refers to the combination of IT infrastructure and IT capability (Raguseo, 2018). Mahesh et al.

(2018) stated that firms with technology resource expertise implement BDT more quickly than others. Therefore, based on the above discussion, the following hypotheses are proposed.

Hypothesis H1. Relative advantage positively influences intention to adopt BDA

Hypothesis H2. Technology competence positively influences intention to adopt BDA

Hypothesis H3. Technology resources positively influences intention to adopt BDA

2.2.2 Influence of organizational factors on BDA adoption intention

Through a systematic literature review on data and information necessary for the adoption of circular manufacturing strategies, one research highlighted the elements of closed-loop supply chain and reverse logistics adoption data, information, and technologies/tools. Although several criteria were proposed to encourage the adoption of BDA to implement various techniques, the study indicated that these aspects be empirically examined and practically confirmed to yield better outcomes (Acerbi et al., 2021). The features of a company that helps or hinders the adoption and execution of an invention are referred to as organizational factors (Gangwar, 2018; Hajiheydari et al., 2021). The most significant criteria for BDA are organizational preparedness, company size, and management support (Wang et al., 2010). By using BDA, Kamioka & Tapanainen (2014) discovered that management engagement and comprehension have been related to competitive advantage. In this study, top management support and firm size have been regarded to be the organizational factors that influence BDA adoption by businesses. The level of understanding and acceptance of a new technology system by top management is referred to as top management support (Maroufkhani et al., 2020).

Top management support is a critical component in fostering a positive environment and allocating sufficient resources to promote the adoption of new technologies (e.g., BDA) (Paley, 2017). The big data implementation necessitates addressing and resolving challenges such as organizational alignment, change management, business process, coordination, and communication, therefore, the involvement of top management support is essential (Gangwar, 2018). Moreover, organizational size is another important factor, which comprises the firm's yearly income and the number of people who might support technology adoption (Mahesh et al., 2018). The larger firms are typically thought to be more resourceful, and as a result, simply it is thought that organizational size has a favourable effect on BDT adoption intention (Raguseo, 2018). Several studies have reported in literature, there is a positive connection between organization size and BDA (Bose & Luo, 2012; Gangwar, 2018; Pan & Jang, 2008; Wang et al., 2010). Therefore, based on the above discussion, the following hypotheses are proposed.

Hypothesis H4. Top management support positively influences intention to adopt BDA

Hypothesis H5. Firm size positively influences intention to adopt BDA

2.2.3 Influence of environmental factors on BDA adoption intention

The external and internal environmental factors are the aspects that organizations may encounter while interacting with their surroundings (Maroufkhani et al., 2020). The industry in which a company operates, its rivals, and government policy or intent are all factors in the environmental context (Verma & Chaurasia, 2019). It issignificant since it has a direct impact on how organizations make decisions (Gangwar, 2018). In the time of adoption decision, the pressures from the organization's rivals, as well as assistance from its vendors, have a more direct influence on BDA (Alsaad et al., 2017). Influences from the external environment that lead the organization to utilize BDA are referred to as “competitive pressure.” It's the pressure that consumers, suppliers, and rivals put on a company in the context of small and medium-sized businesses (Chen et al., 2015).

Several studies have been conducted in literature that reported the importance of competitive pressure in IT adoption (Gangwar, 2018; Lian et al., 2014; Low et al., 2011). Businesses may get a better knowledge of their consumers and markets, inventory visibility, increased operational efficiency, and more accurate data-driven decision making by using BDA (Mourtzis et al., 2016; Verma & Chaurasia, 2019). An organization may decide to implement the same or a comparable innovation when it learns that one of its partners has implemented one to demonstrate its suitability for doing business (Sun et al., 2020). Receiving external supplier assistance is an important factor in BDA, as companies may improve their innovation skills by learning from suppliers and open-source platforms (Maroufkhani et al., 2020). As a result, the firm's trade partner's adoption of BDA may affect the firm's decision to do so. Whereas, when a government promotes businesses in its jurisdiction to embrace big data technologies by providing adequate infrastructure, legal framework, regulatory directives, and assistance, a positive regulatory environment is expected (Sun et al., 2020). Although government regulations might be restrictive, they can also push businesses to adopt new technologies (Maroufkhani et al., 2020). If the government offers legislative support and demonstrates a strong commitment to big data technology, companies will be more likely to use it. Therefore, based on the above discussion, the following hypotheses are proposed.

Hypothesis H6. Competitive pressure positively influences intention to adopt BDA

Hypothesis H7. Trading partner readiness positively influences intention to adopt BDA

Hypothesis H8. Regulatory environment positively influences intention to adopt BDA

2.2.4 Influence of BDA adoption intention on actual use of BDA

The major technology acceptance models such as (TRA, TAM, UTAUT, and UTAUT2) demonstrate a clear link between behavioural intention and technological use (Cabrera-Sánchez &

Villarejo-Ramos, 2020; Venkatesh et al., 2012). A behavioural intention is a strong predictor of an individual's actual usage of technology (Esteves & Curto, 2013). The social sciences literature has shown that behavioural intentions have a direct impact on actual usage, whereas, other disciplines has found that behavioural intentions have a substantial influence on BDA adoption (Shahbaz et al., 2019). Therefore, based on the above discussion, the following hypothesis is proposed.

Hypothesis H9. Intention to adopt BDA positively influences actual use of BDA

2.2.5 Influence of perceived risk as a moderator

A person's perception of risk (PR) is his or her opinion about the uniqueness and magnitude of the risk before using a system (Soon et al., 2016). Perceived risk was formerly described as the perceived uncertainty in a purchasing scenario in consumer research. People's subjective evaluations of performance and effort were characterized as perceived ease of use; generally, there are differences between people's assessments and real performance (Im et al., 2008). In the case of BDA adoption, there may be some ambiguity because the outcome is unknown in the company. Several studies reported the negative impact of perceived risk on BDA adoption intention within the firm. So, this study determined that perceived risk has a negative moderating effect between BDA adoption intention and actual use of BDA and formed the following hypothesis.

Hypothesis H9. Perceived risk negatively moderates the relationship between BDA adoption intention and actual use of BDA.

This study applied the institutional theory as the main theoretical framework supporting our framework since it is applicable and explanatory in our specific context. Aside from the characteristics of the information technology itself, institutional willingness is often required for successful diffusion. Institutional theory is particularly adapted to explaining organizational behavior because of its emphasis on the role of institutional or external settings in affecting organizational behaviors (Sherer et al., 2016; Sun et al., 2020). The following conceptual framework of has been developed based on the above discussion.

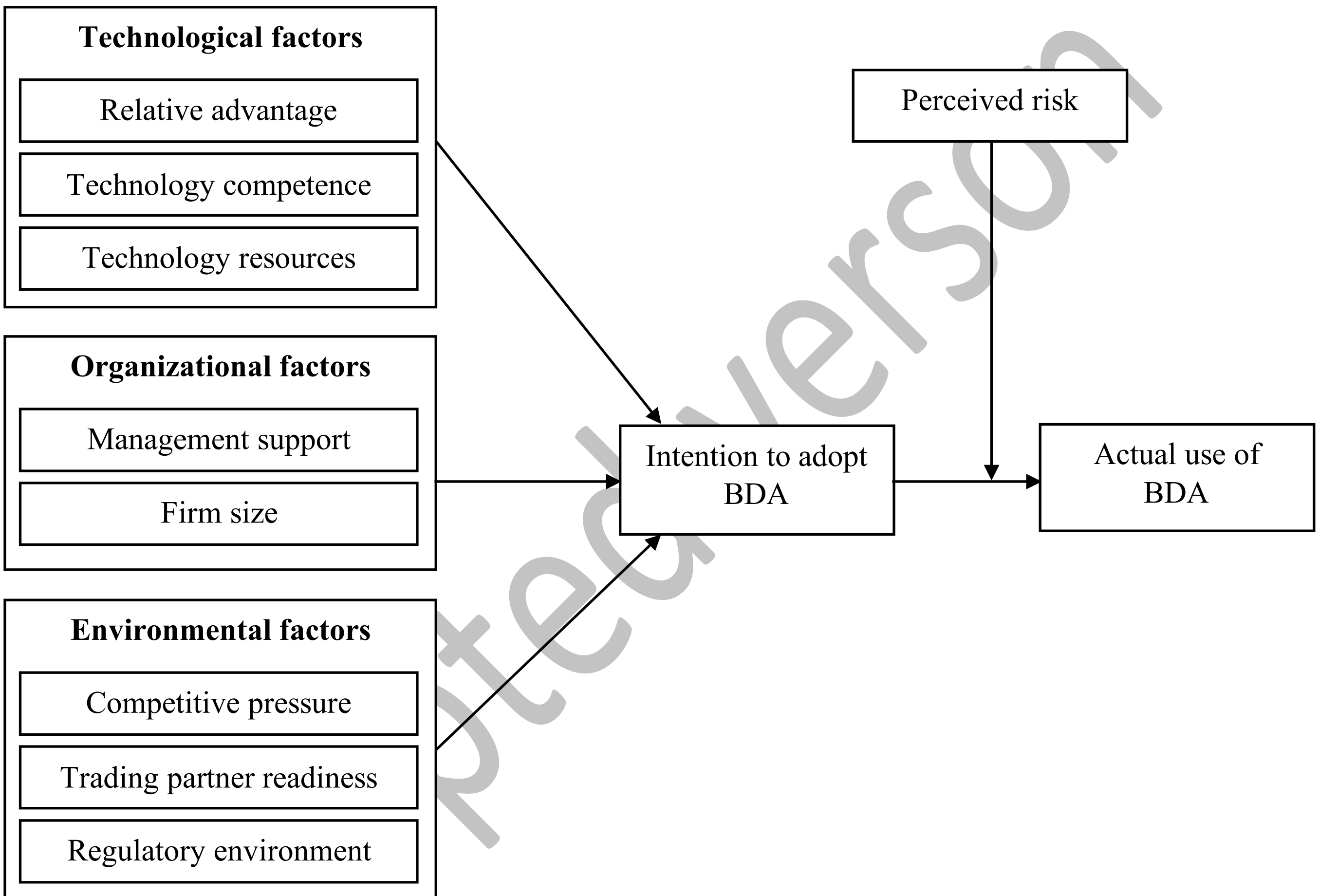

Figure 1. Conceptual framework

3. Methodology

3.1 Sampling and data collection

Responses were collected from participants within manufacturing firms in Amman who hold various managerial positions. The reason for choosing Amman is that it is Jordan's largest city and its capital. A well-structured questionnaire approach was administered for data collection.

Though random sampling has several advantages over the convenience or non-probability sampling approach, which may help to estimate the characteristics of the population (Malhotra, 2010). The sample size was determined based on the guidelines given by (Hair et al., 2019), which is more than 100 for PLS-SEM. A total of 172 valid responses were received used for data analysis.

3.2 Study measures

This study adopted several measurement items from previous studies to measure the constructs in the conceptual model. These constructs were derived from Sun et al., (2020), including relative advantage, technology competence, technology resources, support from senior management, company size, competitive pressure, trading partner readiness, regulatory environment, and adoption intentions. Whereas, perceived risk items were adopted from (Im et al., 2008). Finally, one item was used to measure actual use, which was adopted from (Tsourela & Roumeliotis, 2015). In the questionnaire, a part related to demographic variables was included in the first part of the questionnaire. As part of the assessment, participants rated their degree of agreement or disagreement on a 5-point Likert scale in the second part of the questionnaire. Table 2 illustrated the constructs, associated items, scale and sources.

Table 2. Constructs and measurement items

Constructs	Measurement items
Relative advantage	1. The use of big data could increase opportunities for our company. 2. The use of big data could improve customer services. 3. The use of big data improves the competitiveness. 4. The use of big data could add customers' value. 5. We believe that big data can improve goodwill within our company.
Technology competence	1. We provide excellent IT support through our company. 2. We have a lot of experience supporting big data and business analytics software. 3. We have a good track record of supporting big data and business analytics applications.
Technology resources	1. The network-based applications we have are sufficient. 2. We have flexible systems already in place. 3. Customers can customize our existing systems to suit their needs. 4. We have a well-developed LAN and WAN in our organization.

Top Management Support	1. Big data adoption is likely to be funded by our top management. 2. Big data applications will likely be adopted by our top management in order to gain a competitive advantage. 3. The adoption of big data applications will likely be considered strategic by our top management.
Firm Size	1. 1. In comparison with the industry, my company has high capital. 2. 2. I have a high revenue compared to my industry. 3. 3. We have more employees than the average company in my industry.
Competitive pressure	1. If big data had not been adopted by our firm, we would have been at a competitive disadvantage 2. In the area of business analytics, we are now facing active competition. 3. Big data is becoming an integral part of our competitors' strategies. 4. Our firm may lose an edge over competitors if we fail to embrace big data.
Trading partner readiness	1. There is considerable technical expertise among trading partners. 2. I have been encouraged by my major trading partners to implement big data. 3. Big data was recommended by most trading partners. 4. Technical issues are generally well-understood by trading partners.
Regulatory environment	1. Big data adoption is subsidized by the government. 2. Big data technology is supported by business laws. 3. In promoting big data, the government shows a strong commitment.
Intention to Adopt	1. Considering that my company might have the capability of adopting some form of big data technology, I predict my company would use it. 2. My company would probably make use of some form of big data technology if it had access to it. 3. We are planning to adopt some kind of big data technology within the next 18 months.
Perceived risk	1. BDA is unlikely to be cost-effective. 2. The poor performance of BDA is likely to frustrate me. 3. In comparison with other technologies, using BDA entails more uncertainty. 4. The effectiveness of BDA is unclear.
Actual use	What is the frequency at which your organization has used BDA in the past year?

3.3 The respondents' profile

Demographic variables of the respondents included gender, age, years of experience, education level, position, and the number of employees. As shown in Table 3, male respondents (94.8%) were higher than female respondents (5.2%). Besides, the highest participation was received from respondents with 31 – 40 years old (47.7%), years of experience between 5 and 10 years (40.7%), holding a bachelor degree (81.4%), who were first-line managers (71.5%) and from medium enterprises (47.5%).

Table 3: Demographic profiles of the respondents

Variables	Categories	N	%
Gender	Male	163	94.8%
	Female	9	5.2%
Age	21 – 30 years	44	25.6%
	31 – 40 years	82	47.7%
	41 – 50 years	28	16.3%
	Above 50 year	18	10.5%
Years of experience	Less than 5 Years	44	25.6%
	5-10 Years	70	40.7%
	More than 10 Years	58	33.7%
Education level	Diploma degree	5	2.9%
	Bachelor degree	140	81.4%
	Master's degree and above	27	15.7%
Position	First line managers	123	71.5%
	Middle managers	30	17.4%
	Top managers	19	11.0%
Number of employees	Less than 20 (Small)	51	29.7%
	20 – 99 (Meduim)	79	45.9%
	100 and more (Large)	42	24.4%

4. Results

This study investigates the readiness of manufacturing firms in adopting BDA in Jordon. This section included an analysis of the survey data with different statistical analyses. First, descriptive statistics of the constructs were presented followed by an assessment of multicollinearity. Moreover, the hypothesis tested results from PLS-SEM were presented with the moderation effect..

4.1 Descriptive analysis

Descriptive analyses included mean, standard deviation, skewness, kurtosis and standard error of each of the constructs. The results showed that top management support (M = 4.3488, SD = 1.04407) generated the highest mean value indicating that support from the top management to implement big data was higher among the manufacturing organizations in Jordan. Whereas trading partner readiness (M = 2.3256, SD = 1.03207) generated the lowest mean value indicating that managers thought that their trading partners were not adequately ready for adopting big data in the business processes.

Table 4. Descriptive statistics (n = 172)

Constructs	Mean	Std. Deviation	Skewness	Std. Error	Kurtosis	Std. Error
Relative advantage	4.0512	.86609	-2.175	.185	4.581	.368
Technology competence	3.9826	1.02678	-1.609	.185	2.299	.368
Technology resources	3.8299	1.05191	-1.254	.185	1.163	.368
Top Management Support	4.3488	1.04407	-1.947	.185	2.833	.368
Firm Size	3.8178	.87883	-1.465	.185	2.657	.368
Competitive pressure	3.6875	1.00078	-1.199	.185	.945	.368
Trading partner readiness	2.3256	1.03207	1.067	.185	.072	.368
Regulatory environment	2.9457	1.14947	-.372	.185	-1.345	.368
Intention to adopt	4.2965	.91159	-1.775	.185	2.543	.368
Perceived risk	3.7180	.98103	-1.328	.185	1.560	.368
Actual use	2.38	.998	.609	.185	-.063	.368

4.2 Multicollinearity test

Multicollinearity or a high level of correlations among the independent variables may influence the interpretability of the results. Therefore, any issues with multicollinearity should be assessed before moving to model testing. The results from multicollinearity showed that both of the criteria (e.g., tolerance and variance inflation factor or VIF) generated acceptable results, in other words, tolerance should be above 0.10 and VIF should be below 5 (Hair et al., 2019).

Table 5. Multicollinearity test (Dependent variable: Intention to Adopt)

Constructs	Collinearity statistics	
	Tolerance	VIF
Relative advantage	.389	2.569
Technology competence	.285	3.508
Technology resources	.315	3.176
Top Management Support	.295	3.386
Firm Size	.364	2.744

Competitive pressure	.353	2.832
Trading partner readiness	.931	1.074
Regulatory environment	.699	1.431

4.3 Partial Least Square Structural Equation Modelling (PLS-SEM)

Structural equation modelling with a partial least square approach was conducted using SmartPLS software version 3 (Ringle, Christian M., Wende, Sven, & Becker, 2015). First, the reliability and validity of the measurement model were performed. Moreover, the structural model was run to test the proposed hypotheses along with the moderation analysis.

4.3.1 Assessment of the measurement model

The measurement model was assessed with construct reliability, convergent validity and discriminant validity. As shown in Table 6, all the constructs had Cronbach's alpha and composite reliability above 0.70 and thus acceptable (Hair et al., 2019). Convergent validity was confirmed with values of factor loading above 0.70 and average variance extracted (AVE) above 0.50 (Hair et al., 2019). There was an item in trading partner readiness (item 4) that was removed due to negative and low factor loading.

Table 6. Construct reliability and validity

Constructs	Items	Factor loadings	Cronbach's alpha	Composite reliability	AVE
Competitive pressure	CR.1	0.957	0.976	0.982	0.932
	CR.2	0.960			
	CR.3	0.971			
	CR.4	0.974			
Firm size	FS.1	0.955	0.949	0.967	0.908
	FS.2	0.957			
	FS.3	0.946			
Intention to adopt BDA	INT.1	0.947	0.922	0.951	0.865
	INT.2	0.910			
	INT.3	0.934			
Perceived risk	PR.1	0.944	0.957	0.969	0.887
	PR.2	0.926			
	PR.3	0.948			

	PR.4	0.948			
Relative advantage	RA.1	0.928	0.959	0.968	0.858
	RA.2	0.901			
	RA.3	0.921			
	RA.4	0.941			
	RA.5	0.940			
Regulatory environment	RE1	0.980	0.981	0.987	0.963
	RE2	0.986			
	RE3	0.976			
Technology competence	TC.1	0.984	0.980	0.987	0.962
	TC.2	0.978			
	TC.3	0.980			
Management support	TMS.1	0.980	0.972	0.982	0.947
	TMS.2	0.959			
	TMS.3	0.981			
Trading partner readiness	TPR1	0.976	0.962	0.920	0.797
	TPR2	0.973			
	TPR3	0.701			
Technology resources	TR.1	0.983	0.983	0.987	0.950
	TR.2	0.969			
	TR.3	0.972			
	TR.4	0.976			

As suggested by Fornell & Larcker (1981), inter-construct correlation coefficients should be lower than the square root of AVE to provide evidence of discriminant validity. As illustrated in Table 7, all the values of AVE's square roots were higher than the correlation coefficient among the constructs.

Table 7. Discriminant validity

Constructs	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Competitive pressure	0.965									
2. Firm size	0.764	0.953								
3. Intention to adopt BDA	0.204	0.281	0.930							
4. Management support	0.548	0.539	0.429	0.973						
5. Perceived risk	0.532	0.539	0.283	0.482	0.942					
6. Regulatory environment	0.434	0.358	0.197	0.417	0.368	0.981				

7. Relative advantage	0.638	0.631	0.351	0.684	0.580	0.451	0.926			
8. Technology competence	0.471	0.503	0.404	0.779	0.473	0.396	0.634	0.981		
9. Technology resources	0.471	0.513	0.381	0.746	0.484	0.450	0.623	0.786	0.975	
10. Trading partner readiness	0.121	0.130	0.060	0.027	0.143	0.198	0.073	0.133	0.017	0.892

4.3.2 Assessment of the structural model

After testing the reliability and validity of the measurement model, the structural model was investigated. A bootstrapping method was used with 1000 sub-samples in SmartPLS version 3. The values of r square showed that all the independent constructs explained 21.5% variations in adoption intention which explained 28.9% variations in the actual use of BDA. These r square values suggest small effects exerted by the constructs (Hair et al., 2019).

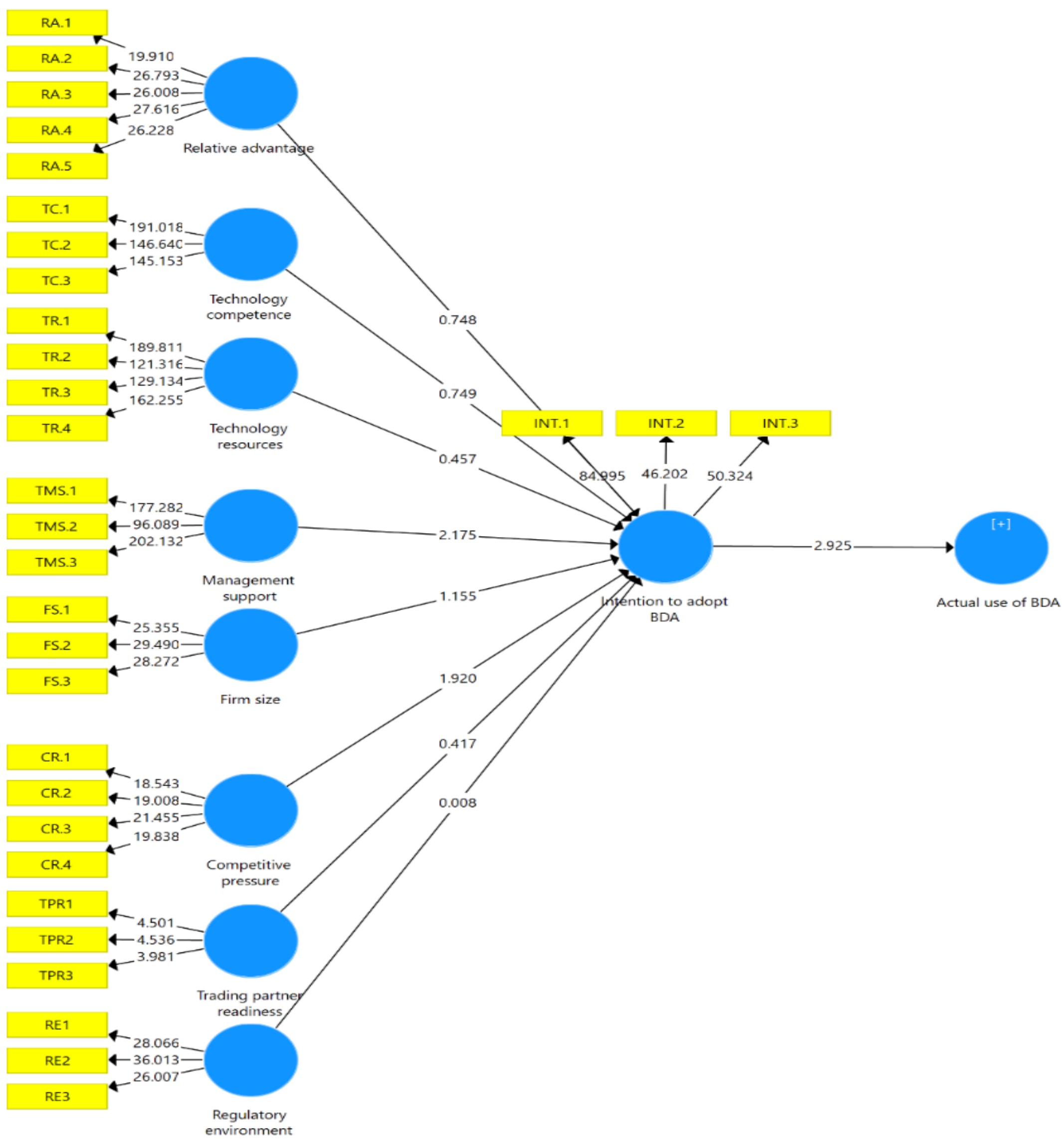

Figure 2. Model estimation

The results of the structural model were illustrated in Table 8 including beta or path coefficients, t statistics, p-value and the hypotheses. The findings showed that intention to adopt BDA was influenced significantly by management support (beta = 0.267, $p < 0.05$) and competitive pressure (beta = -0.186, $p < 0.10$). The influence of management support on intention to adopt BDA was positive whereas the influence of competitive pressure was negative. Moreover, intention to adopt BDA significantly and positively influenced actual use of BDA (beta = 0.200, p

< 0.01). The results of moderation showed that the influence of perceived risk as a moderator was not statistically significant on the relationship between BDA adoption intention and actual use of BDA.

Table 8. Results of structural model

Paths	Beta	T Statistics	P Values	Results
H1. Relative advantage -> Intention to adopt BDA	0.100	0.748	0.455	Rejected
H2. Technology competence -> Intention to adopt BDA	0.106	0.749	0.454	Rejected
H3. Technology resources -> Intention to adopt BDA	0.057	0.457	0.648	Rejected
H4. Management support -> Intention to adopt BDA	0.267	2.175	0.030	Supported
H5. Firm size -> Intention to adopt BDA	0.129	1.155	0.248	Rejected
H6. Competitive pressure -> Intention to adopt BDA	-0.186	1.920	0.055	Supported
H7. Trading partner readiness -> Intention to adopt BDA	0.036	0.417	0.677	Rejected
H8. Regulatory environment -> Intention to adopt BDA	0.001	0.008	0.993	Rejected
H9. Intention to adopt BDA -> Actual use of BDA	0.200	2.925	0.004	Supported
Moderating effects				
H10. Moderating effect-> Actual use of BDA	0.056	1.356	0.175	Rejected

5. Discussion

In this study, we explore the factors that affect managers' intentions to adopt BDA in their organizations. Several studies have investigated the adoption of BDA in different organizations (Behl et al., 2019; Gangwar, 2018; Im et al., 2008; Kwon et al., 2014; Mahesh et al., 2018; Maroufkhani et al., 2020; Shahbaz et al., 2019; Soon et al., 2016; Sun et al., 2020; Tsourela & Roumeliotis, 2015; Venkatesh et al., 2012; Verma & Chaurasia, 2019; Villarejo Ramos & Cabrera-Sánchez, 2019). Previous studies extensively investigated user acceptance intention of big data (Im et al., 2008; Kwon et al., 2014), however, examining actual use behaviour remained nascent (Tsourela & Roumeliotis, 2015). Therefore, this study sheds light on the actual use behaviour of BDA by investigating the moderating role of perceived risk to dig deeper into the user acceptance of technology such as BDA.

The findings showed that management support (beta = 0.267) has the largest and significant influence on big data adoption intention. Whereas, the regulatory environment (beta = 0.001) has the lowest and insignificant effect on adoption intention. Moreover, the influence of competitive pressure (beta = -0.186) on BDA adoption intention was significant but it was negative. The findings of the study endorsed by previous studies such as Maroufkhani et al. (2020) found a significant influence of top management support on BDA adoption. In line with the findings of the present study, several studies (Gangwar, 2018; Sun et al., 2020; Verma & Chaurasia, 2019) also found that management support positively and significantly influenced big data adoption. However, they found a positive influence of competitive pressure on the adoption of big data, which contrasts with the current finding of the study. Verma & Chaurasia (2019) examined that a big number of factors such as compatibility, top management support, technology readiness, organizational data environment and trading partner readiness had insignificant influence on non-adopters intention to adopt BDA. This can be a reason (e.g., lack of big data adoption among the participant organizations) why many of the factors are insignificant in the present findings. This study revealed two primary factors that have an influence on the intention to adopt BDA, including top management support and competitive pressure. To enhance the intention to adopt BDA, it should be supported by top management and viewed as an essential strategic decision for the organization. Furthermore, top management should think that BDA is critical to attaining a competitive edge. As for the competitive pressure factor, it appears that BDA will be implemented if they confront active competition. Furthermore, BDA intention will increase if BDA becomes an integral part of our rivals' strategies, and you may lose a competitive advantage if the organization does not embrace it. The study found that respondents had little agreement on the importance of trade partner readiness and regulatory in increasing their intention to adopt BDA. The readiness of a trading partner may necessitate significant technological skills. Furthermore, trading partners may not urge enterprises to use BDA, and BDA implementation may be discouraged if it is not recommended by them. In terms of the regulatory environment, it is clear that BDA is not funded by the government and is not protected by corporate regulations. This suggests that the government is not making a concerted effort to promote BDA adoption.

It has been shown that intentions to adopt BDA have a significant and positive influence on actual usage. The finding is similar to that of previous studies (Shahbaz et al., 2019; Tsourela & Roumeliotis, 2015) who found that the actual use of technology-based services was significantly and positively influenced by the intention to use. Finally, the study does not find any significance of perceived risk as a moderating variable, however, the result is not consistent with that of Soon et al. (2016) who found a significant and negative impact of perceived risk on BDA adoption. Being consistent with the current findings, Villarejo Ramos & Cabrera-Sánchez (2019) observed that intention to adopt BDA influenced usage behaviour and the effect of perceived risk is insignificant on adoption intention.

The study has several implications for the theory; this study contributes to the body of knowledge on BDA by examining the various factors believed to be involved in BDA adoption intention and investigating the relationships between these factors and organizational BDA adoption. Our contribution has accurately identified and described the linked causal pathways, or antecedent configurations, that might impact organizational intention to adopt BDA. The findings show that two of the eight factors significantly determined the intention to use BDA. Furthermore, it was discovered that the moderating effect of perceived risk had no significant effect on the link between BDA intention to use and actual usage of BDA. Our main findings therefore give a better understanding of the enablers of BDA adoption, particularly the categorization of BDA components into three categories, which promotes the improvement of these categories to implement BDA. The findings of the empirical study analysis enhance our understanding of how to adopt BDA in the manufacturing sector and take into account other factors that make organizations well prepared to adopt BDA in their operations.

The study has several implications for practitioners. First, this study finds that the top management support was the only variable leading to BDA adoption intention among the managers of Jordan. Therefore, top management should be targeted for the successful adoption of BDA among the manufacturing organizations in Jordan. However, other theoretically important variables are found to have no significance, so, future studies are needed to find out the reasons behind the phenomena. Second, competitive pressure has a positive significant effect on BDA adoption, therefore, manufacturing firms in Jordan should believe that BDA is an important tool to have a competitive advantage during a fierce competition in the market. Third, moderating influence of perceived risk cannot be proved in this study where past studies showed that perceived risk has negative consequences while adopting technology. Hence, future researchers may research to examine moderation of perceived risk in different study contexts. Fourth, Manufacturing forms in Jordan should believe in the relative advantage of BDA, which includes more opportunities for the enterprise, improved customer services, more competitiveness, increased customer value, and improved corporate goodwill. Furthermore, in order to embrace BDA, it is critical to give outstanding IT support within the firm and hire staff with extensive expertise supporting big data and business analytics software. Furthermore, manufacturing firms need have a proper infrastructure to operate BDA apps smoothly. Companies must dedicate some budget to IT development in terms of infrastructure and personnel in order to do so. Another practical consideration is the mindset of adopting BDA. Managers and staff in the manufacturing sector should understand that investing in BDA is a cost-effective learning experience that will yield fruit over a period of time. Finally, this study proves that behavioral intention successfully leads to the actual use of BDA. The obvious link between intention and actual use was less obverted in the past studies, which has been examined in this study.

6. Conclusion

The study examines how the model of technology-organization-environment impacts adoption intentions towards BDA. Furthermore, the study also helps to provide additional insight into the relationship between intention and actual use of BDA in the context of risk perception, as well as the influence of intentions on actual use of BDA towards sustainable development. The study found that two constructs, top management support and competitive pressure, had a significant effect on the intention to adopt BDA. Furthermore, the study found no significant moderating effect for perceived risk of BDA on the relationship between intention to use BDA and actual usage. Finally, the study revealed that the intention to use BDA had a considerable impact on its actual use. However, this study has some limitations. Data from 172 respondents utilizing convenience sampling was collected for data analysis. Future studies should undertake studies with a larger sample size with random sampling for better generalizations of the results. Moreover, the majority of the proposed relationships were found to be insignificant in this study. The reasons can be attributed to lower sample size or lack of a clear understanding of big data among the respondents. However, further studies in other geographies, demographics and industries should be conducted to verify the results. Moreover, replicating the framework with measuring its impact on sustainable performance.

Ethics Declarations

Ethics approval

The data used in this study did not involve any human or animal subjects.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of Data and Materials

The participants in the survey presented in this paper was anonymous, and only their organizational positions were indicated in the results. The data used in the current study can be provided on request.

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Key Questions

What are the determinants of BDA adoption for manufacturing companies?

What are the significant factors that affect the intention to adopt BDA by manufacturing companies?

How BDA perceived risk affects the relationship between intention to adopt BDA and actual adoption of BDA?

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