

Uncertain Supply Chain Management

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Adoption enablers of big data analytics in supply chain management practices: the moderating role of innovation culture

Luay Jum'a^{a*} and Sona Kilani^a

^aLogistic Sciences Department, German Jordanian University, Amman, Jordan

ABSTRACT

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The enablers of Big Data Analytics (BDA) on the BDA adoption intention of consumer goods' retailing firms were measured in this study along with innovation culture as a moderator. Based on a literature review, six BDA adoption intention enablers: financial readiness, perceived advantages, top management support, IT infrastructure, technology sophistication, and data quality were identified. The study collected data from different levels of managers in the consumer goods' retailing sector in Jordan to test the proposed study framework. To obtain primary data, a quantitative method was used, and a survey (structured questionnaire) was conducted. SmartPLS version 3.3 was used to analyze and test the proposed study model, which included 211 respondents. Three BDA enablers, including perceived advantages, top management support, and IT infrastructure, were found to have a statistically significant effect on BDA adoption intention in their supply chain operations. Furthermore, the relationship between financial readiness and BDA adoption intention was significantly moderated by innovation culture. This research model can be used to determine the challenges and enablers to BDA adoption in supply chain operations for both developed and developing countries. Future research may replicate the model in various sectors or the same sector in different countries.

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1. Introduction

The rapid advancement of information technology has altered the competitive landscape in a number of businesses. Big data (BD), which is defined by volume, variety, velocity, and value (Tan et al., 2015), is a key component of different technological breakthroughs. With the advancement of the BD era, big data analytics (BDA) has gotten a lot of attention from academics and professionals, who have realized the tremendous commercial value that BD can offer to a company (Chen et al., 2012). Despite the potential for BDA to improve marketing efficiency, decision-making process, and business performance (Bahrami & Shokouhyar, 2021), its influence on supply chain (SC) management remains unknown. Because firms' logistics and SC operations can have a significant impact on its overall performance, improving the SC process through BDA is critical (Gunasekaran et al., 2017). The literature on supply chains has mostly focused in the last few years on firm performance with BDA capabilities (Zhong et al., 2016; Maheshwari et al., 2021), BDA and the influence on supply chain and organizational performance integration (Tan et al., 2015; Gunasekaran et al., 2017). It also looked at the impact of BDA on company performance (Yasmin et al., 2020) and BDA's commitment to world-class, environmentally friendly manufacturing (Fosso Wamba et al., 2017). However, there are significant gaps in the BDA literature on SC, such as the development of models to assist firms in implementing BDA initiatives. Furthermore, there are no studies using empirical research in developing countries (Maheshwari et al., 2021) such as Jordan to identify and spot the key challenges and hurdles to BDA implementation. Organizations are unsure of the professional capability of using BDA or whether their current proficiencies are adequate for implementing a BDA in supply chain management (SCM) (Queiroz & Telles, 2018). The literature on BDA is insufficiently broad, and there are no models or frameworks for determining whether or not big data can be implemented

* Corresponding author

E-mail address luay.juma@gju.edu.jo (L. Jum'a)

effectively and efficiently. In this context, it is reasonable to conclude that the Jordanian literature on BDA in SCM is limited (Queiroz & Telles, 2018; Bahrami & Shokouhyar, 2021). The purpose of this study is to address the following question in order to enhance knowledge and overcome comprehension gaps connected with BDA in SCM:

RQ1. What are the enablers of BDA related to SCM practices in the consumer goods' retailing sector in Jordan?

RQ2. How do BDA enablers related to SCM practices affect the BDA adoption intention of firms in the consumer goods' retailing sector in Jordan?

RQ3. Does innovation culture moderates the relationship between BDA enablers and the BDA adoption intention of firms in the consumer goods' retailing sector in Jordan?

2. Literature review

2.1. *Big Data Analytics (BDA)*

Huge data are produced and recorded by new technologies as a result of the rise of social networking sites, and mobile technology (Chen et al., 2012). Every day, businesses are confronted with many types of data, including keywords and logs information, trade transactions, and consumers' related content (Mikalef et al., 2020). Given the high size, speed, and diversity characteristics of data generated through multiple sources of information, the term "big data" (BD) was coined to represent the immensity and complexity of data, which often necessitates organizations improving their handling and analyzing capabilities (Mikalef et al., 2020). To benefit from business insights of BD, firms must implement two stages: data acquisition and data analysis (Gandomi & Haider, 2015). From data capture, recording, mining, cleansing, and explanation through assimilation, accumulation, and display, data management is a continuous process. Modeling, analysis, and interpretation are all part of analytics (Gandomi & Haider, 2015). BDA is defined as "a new generation of technologies and architectures, designed to cheaply extract value from very large quantities of a wide range of data, by allowing high-velocity collection, discovery, and/or analysis," according to the author (Gandomi & Haider, 2015). BDA has two points of view: data and analysis (Maheshwari et al., 2021). The data provides the information and technology for analytical operations, whereas the analysis provides companies with important strategic insights that, when used correctly and appropriately, may play a vital part in the decision-making process. To get the most out of this new information technology, you'll need to put money into infrastructure, management, and staff skills (Fosso Wamba et al., 2017). Human talents (employee knowledge and skills) are also required throughout the whole BD utilization process, in addition to real (cost - effective) and intangible (organizational culture and learning) resources (Queiroz & Telles, 2018). For example, BDA may help companies retain sustainable competitive advantages by giving crucial consumer insights that favorably impact firms' dynamic and adaptable power to enhance the value creation of marketing activities and acquire advantages over rivals (Benoit et al., 2020). Thus, BDA can play a critical role in assisting businesses flourish in an increasingly competitive environment, whether from a strategic or operational one. There are many enablers facing BDA adoption in SCM practices for the consumer goods' retailing sector in Jordan as follows:

2.2. *Financial Readiness (FR)*

Financial readiness relates to the possible available funds that are arranged to pay for the expenses of learning and integrating new systems (Maduku et al., 2016), and it is one of the most important aspects in a company's adoption of technical innovation (Lai et al., 2018). The significance of financial dimension cannot be underestimated and be overstated (Jere & Ngidi, 2020), given that, in the absence of adequate financial resources, companies cannot purchase IT equipment or competent BDA staff. Massive financial resources are required for the process of beginning and funding the ongoing costs of BDA. More significantly, with enough cash, businesses can better survive the interruptions that occur with the adoption and deployment of new technologies (Lai et al., 2018; Jum'a et al., 2022).

2.3. *Perceived Advantages (PA)*

The technical dimension is concerned with the qualities of the technology that is supposed to have a favorable or negative influence on the choice to embrace a new technology. When cloud computing first became available, studies were conducted to assess the choice to embrace this new technology (Gunasekaran et al., 2017). Furthermore, Hus et al. (2014) used perceived advantages and commercial aspects as technology variables to conduct a study to analyze the cloud computing adoption issues. Similarly, the study uses perceived advantages (Gunasekaran et al., 2017) and technological complexity (Queiroz & Telles, 2018) as major determinants of BDA adoption based on previous research. Furthermore, because data is the cornerstone of BDA, the study uses data quality as a dimension in the study. Concerning costs, we take them into account in the framework of the organization's financial readiness. The perceived advantages of BDA technology reflect the extent to which it can help the company (Zhong et al., 2016). Concerning the research aim, we primarily focus on the benefits BDA may offer to SCM, such as quicker response rate to changes in the business environment, more precise anticipating and controlling SC hazards, cooperation with other SC members, and decreasing SC waste (Gunasekaran et al., 2017). More significantly, BDA provides companies with a valuable tool for reducing the inferiority created by asymmetric information, because firms may fully utilize different sources of data acquired to evaluate changes and trends that occur with competitors (Zhong et al., 2016; Lai et al., 2018). When business executives see the distinguishing advantages of BDA, they are more likely to experiment with this innovative technology.

2.4. Top Management Support (TMS)

Maduku et al. (2016) used TMS, planned amount of capital, and availability of staff competency as organizational variables to develop a framework to better understand the purpose of SMEs to use mobile marketing. Wamba et al. (2016) discovered that company size has an impact on firm structure and had a favorable effect on the intention to use RFID technology. The term “top management support” refers to “the extent to which top management recognizes the relevance of the IS function and is active in IS activities” (Lai et al., 2018). TMS's assistance significantly helps create a welcoming atmosphere and the provision of appropriate resources to expedite the adoption of information technology advances (Maduku et al., 2016; Jum'a et al., 2022). As a result, how much care the BDA technology receives from TMS will have a direct impact on the communication and usage of BDA inside the company (Sivarajah et al., 2017).

2.5. Information Technology Infrastructure (IT)

IT infrastructure and competencies refer to a company's concrete and intangible personnel resources, abilities, and experience resources for implementing IT innovations (Maduku et al., 2016). It has been empirically demonstrated that there is a favorable link between information technology embracing and IT infrastructure and competencies (Hsu et al., 2014; Maheshwari et al., 2021). Furthermore, Maheshwari et al. (2021) discovered that a business with greater IT capabilities had a higher likelihood of adopting cloud services. An atmosphere favorable to data analysis is created with a very good IT infrastructure that includes hardware, software, and knowledge (Maduku et al., 2016), with which the business may successfully establish the BD business venture. Furthermore, prior research has shown that the better a company's IT capabilities, the more likely it is to adopt new technologies (Hsu et al., 2014). As a result, it is thought that a company's IT infrastructure and skills might improve the likelihood of BDA adoption.

2.6. Technology Sophistication (TS)

The complexity of BDA technology in terms of understanding and application for the organization is referred to as its technological sophistication (Jere & Ngidi, 2020). BD is not a useless idea; rather, it encourages businesses to take action in order to have important strategic actions. Firms, for example, are expected to educate or hire BDA personnel, fund BDA operations, and promote the expansion of BDA across organizational activities (Jere & Ngidi, 2020). TS prevents firms from having new technological innovations, introducing challenges such as unsuitability with current firm' systems (Yasmin et al., 2020), the ability of firm's infrastructure to update systems (FossoWamba et al., 2016), data computational capacity, and high capital and running costs of embracing BDA and related information systems (FossoWamba et al., 2016).

2.7. Data Quality (DQ)

Data quality denotes the point to which the data required for analysis are available, reliable, and comprehensive (Lai et al., 2018). Businesses should establish numerous competencies like data mining or text mining, data analysis, modeling, and compilation, as well as define quantitative and qualitative statistical tools to flourish in the era of BD (Bahrami & Shokouhyar, 2021) to serve as the foundation template for subsequent analyzing work. The availability of diverse data for a given business is critical to the success of the BDA implementation. The volume of information for SC management that is available in the firm's data repository is referred to as data completeness, whereas data consistency refers to keeping data uniform as it moves and is exchanged among SC partners (Akter et al., 2016). When it comes to data quality, the most essential two aspects are data consistency and data completeness (Akter et al., 2016; Sivarajah et al., 2017). Organizations will have more confidence in effectively using BDA in everyday operations if their data is of higher quality.

2.8. Innovation Culture (IC)

The culture of an organization, according to Eldridge and Crombie (2013), is the unique combination of rules, values, beliefs, and behavioural patterns that describe the way in which groups and individuals collaborate to accomplish goals. Innovation culture has received a lot of attention in both academic and practical contexts as an important type of organizational culture (Ataei and Sharifirad, 2012). Dobni (2008) defined innovation culture as the spirit and content formed by enterprises during the process of innovation and different managerial activities, including the enterprise's innovation values, codes of conduct, institutional practices, material and cultural environment, and other elements related to innovation. In fact, from a cultural standpoint, the key components of innovation include originality, flexibility and acceptance to new ideas, risk-taking, and an entrepreneurial mindset. Thus, in contrast to a bureaucratic culture, an innovation culture frequently encourages the employees to think, improve communication and knowledge, embrace innovative thoughts, and so on (Ali-Hassan et al., 2015). Furthermore, if firms can create a favorable organizational climate, they are more likely to achieve greater motivation, commitment, and employee engagement (Shanker et al., 2017; Yu et al., 2014), and workforce trust can be built as a result of this process (Ruppel and Harrington, 2000). Given that the volatile business climate, technological advancements, and intense competition have an impact on management and organizational continuity, organizations are required to re-evaluate their practices to face these difficulties and have an intention to incorporate BDA in their SC operations. As a result, in order for an organization to be innovative, a culture of innovation and creativity should be fostered in order to promote the adoption of BDA (Horibe, 2016).

2.9. The research model and hypothesis development

The proposed research model presented in Figure 1 was adapted from prior research discussed in the literature review part. The enablers of adopting BDA consisted of six dimensions adopted from prior research: financial readiness (Lai et al.,

2018); perceived advantages (Gunasekaran et al., 2017); top management support (Wamba et al., 2016); IT infrastructure (Hsu et al., 2014); technology sophistication (Maduku et al., 2016; Maheshwari et al., 2021); and data quality (Lai et al., 2018). Additionally, innovation culture was adopted from (Ma et al., 2021) and intention to adopt BDA were adopted from (Mishra et al., 2014).

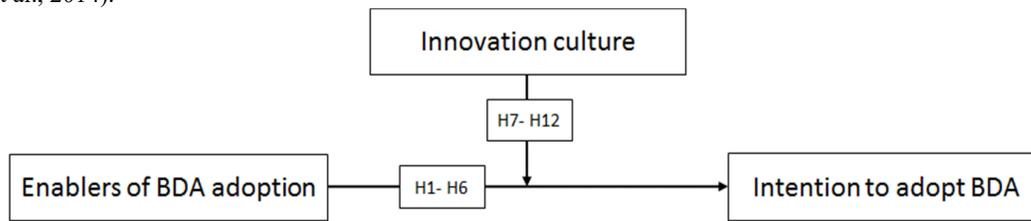


Fig. 1. The research model

The research model was based on the literature review of BDA enablers, and consequently, the following hypotheses was formulated in the context of consumer goods' retailing sector:

- H₁:** *Financial readiness significantly affects intention to adopt BDA.*
- H₂:** *Perceived advantages significantly affect intention to adopt BDA.*
- H₃:** *Top management support significantly affects intention to adopt BDA.*
- H₄:** *IT infrastructure significantly affects intention to adopt BDA.*
- H₅:** *Technology sophistication significantly affects intention to adopt BDA.*
- H₆:** *Data quality significantly affects intention to adopt BDA.*
- H₇:** *Innovation culture moderates the relationship between the financial readiness and the intention to adopt BDA.*
- H₈:** *Innovation culture moderates the relationship between the perceived advantages and the intention to adopt BDA.*
- H₉:** *Innovation culture moderates the relationship between the top management support and the intention to adopt BDA.*
- H₁₀:** *Innovation culture moderates the relationship between the IT infrastructure and the intention to adopt BDA.*
- H₁₁:** *Innovation culture moderates the relationship between the technology sophistication and the intention to adopt BDA.*
- H₁₂:** *Innovation culture moderates the relationship between the data quality and the intention to adopt BDA.*

3. Methodology

The survey method is used in this investigation. Surveys are widely used in logistics and SC studies (Aggestam et al., 2017, Jum'a, 2020). For measurement, a five-point Likert scale was devised, with values ranging from strongly disagree (1) to strongly agree (5). (Lai et al., 2018; Bahrami & Shokouhyar, 2021). To put the survey to the test, two SC experts were asked to evaluate the questionnaire tool for knowledge, clarity, and validity of the variables' elements (Bahrami & Shokouhyar, 2021). Following a pilot study, the design was tweaked based on prior input to increase reliability. Data was gathered face-to-face, via phone conversations, or by e-mail. The survey was distributed to supply chain specialists. In Jordan, survey invitations were distributed to the Consumer Goods Retailing Sector. The data gathering procedure was carried out by a specialist data collection company from April to July 2021, and a total of 211 questionnaires were received. The questions received were guaranteed to be full surveys. Retailing sector in Jordan is considered as one of the least saturated in the region. This sector is expected to develop rapidly over the few coming years. According to the Department of Statistics in Jordan, the retailing and wholesaling sector accounts for 9.3 percent of the GDP. Consumer goods constitute the largest part of the retailing sector in Jordan. However, many challenges are facing the growth of this sector.

4. Results and discussion

4.1. Demographics Statistics

Fig. 2 shows the respondents' demographic information, including gender, years of experience, degree of education, position, and number of employees.

According to the number of employees in each, the sample was divided into small, medium, and large organizations—medium (53 percent), small (32 percent), and large (15 percent) organizations.

4.2. Structural Equation Modelling (SEM)

SEM technique was adopted to perform data analysis of this study. Data Analysis in SEM comprises two stages. First, the measurement model was assessed to examine the internal consistency, reliability and validity of the construct to illustrate whether the constructs of the study are consistent and reliable. After that structural assessment model was conducted to examine the proposed hypotheses and path. This research study employs a partial least square modeling technique (PLS-SEM). The statistical software SmartPLS version 3.3 was used for data analysis (Ringle et al., 2015).



Fig. 2. Sample description of the study

4.3. Measurement Model

In the first step of PLS SEM, measurement model of study was investigated as per the recommendation of (Henseler et al., 2016). In the measurement model "Individual item reliability, internal consistency, content validity, convergent validity and discriminant validity have to be examined". Factor loadings can range from -1.0 to +1.0 with higher absolute values indicating a high correlation of the items with the underlying factors" (Pett et al., 2003, P.299). According to Hair et al. (2019) proposed factor loadings of construct should be greater than 0.7 which means that the items of construct represent 70% of that construct. According to Creswell (2009), a research instrument is reliable if the scale produces the same results in the same conditions. The higher reliability of the scale represents more precision and accuracy. Hair et al. (2019) suggest that the value of Cronbach's is higher than 0.70 to determine the internal consistency of the construct. Table 1 shows that the Cronbach's alphas of all constructs are greater than 0.7. Therefore, internal consistency of each variable is established.

Another method for checking the internal reliability and consistency of a scale is composite reliability. According to (Hair et al., 2019), the Value of CR greater than the range between 0.60 to 0.70 is considered acceptable. Table 2 highlights that the composite reliability of each latent construct is above 0.70 thus internal consistency is established. Similarly, Table 2 indicates that the composite reliability of the construct is also greater than 0.700. Hence construct reliability is accepted of both constructs.

4.4. Convergent & Discriminant Validity

In the second step of measurement assessment model validity of constructs are measured. There are two types of validity which include convergent and discriminant validity. Convergent validity refers to has defined as a concept in which an indicator used to measure each latent variable should be related to each other based on the theoretical support from the past research (Hair et al., 2019). The average variance extracted (AVE) is used for determining convergent validity for all constructs. In this study, AVE for all the variable constructs is above 0.50. Thus, convergent validity has been established. Table 2 shows the AVE values of all constructs.

Discriminant validity is the degree to which measures of different concepts are distinct. The notion is that if two or more concepts are unique, then valid measures of each should not correlate high" (Bagozzi et al., 1991, p.225). There are three ways to determine discriminant validity of construct in SmartPLS which includes Fornell & Larcker criterion, Cross loadings and Heterotrait-Monotrait. Fornell-Larcker (1981) proposed that to establish the discriminant validity of constructs the square root of AVE of each variable in the research model must be higher than the correlation of the same variable with

others. Table 2 illustrates that the square root of AVE of each construct is greater than the diagonal values below. Similarly, Table 2 illustrates the square root of AVE of each construct is greater than the diagonal below. Hence, discriminant validity is established.

Table 2
Results of the Assessment of measurement model

| Variables | Items | Outer loadings | Cronbach's Alpha | CR | AVE |
|------------------|-------|----------------|------------------|-------|-------|
| DQ | | | 0.994 | 0.995 | 0.960 |
| | DQ1 | 0.980 | | | |
| | DQ2 | 0.980 | | | |
| | DQ3 | 0.958 | | | |
| | DQ4 | 0.986 | | | |
| | DQ5 | 0.986 | | | |
| | DQ6 | 0.981 | | | |
| | DQ7 | 0.983 | | | |
| | DQ8 | 0.985 | | | |
| FR | | | 0.988 | 0.990 | 0.944 |
| | FR1 | 0.975 | | | |
| | FR2 | 0.969 | | | |
| | FR3 | 0.971 | | | |
| | FR4 | 0.964 | | | |
| | FR5 | 0.975 | | | |
| | FR6 | 0.975 | | | |
| IC | | | 0.962 | 0.972 | 0.898 |
| | IC1 | 0.955 | | | |
| | IC2 | 0.930 | | | |
| | IC3 | 0.952 | | | |
| | IC4 | 0.952 | | | |
| Intention | | | 0.964 | 0.972 | 0.875 |
| | INT.1 | 0.953 | | | |
| | INT.2 | 0.964 | | | |
| | INT.3 | 0.960 | | | |
| IT | | | 0.984 | 0.986 | 0.900 |
| | IT1 | 0.915 | | | |
| | IT2 | 0.940 | | | |
| | IT3 | 0.960 | | | |
| | IT4 | 0.935 | | | |
| | IT5 | 0.925 | | | |
| PA | | | 0.951 | 0.965 | 0.873 |
| | PA1 | 0.931 | | | |
| | PA2 | 0.934 | | | |
| | PA3 | 0.946 | | | |
| | PA4 | 0.951 | | | |
| | PA5 | 0.947 | | | |
| | PA6 | 0.967 | | | |
| | PA7 | 0.952 | | | |
| | PA8 | 0.961 | | | |
| TMS | | | 0.901 | 0.930 | 0.768 |
| | TMS1 | 0.916 | | | |
| | TMS2 | 0.944 | | | |
| | TMS3 | 0.950 | | | |
| | TMS4 | 0.926 | | | |
| TS | | | 0.899 | .890 | .716 |
| | TS1 | 0.886 | | | |
| | TS2 | 0.848 | | | |
| | TS3 | 0.856 | | | |
| | TS4 | 0.914 | | | |

Table 2
Fornell-Larcker criterion

| | DQ | FR | IC | IT | Intention | PA | TMS | TS |
|------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| DQ | 0.980 | | | | | | | |
| FR | 0.449 | 0.972 | | | | | | |
| IC | 0.407 | 0.710 | 0.947 | | | | | |
| IT | 0.542 | 0.615 | 0.576 | 0.935 | | | | |
| Intention | 0.392 | 0.494 | 0.564 | 0.562 | 0.959 | | | |
| PA | 0.580 | 0.448 | 0.488 | 0.555 | 0.486 | 0.949 | | |
| TMS | 0.268 | 0.147 | 0.202 | 0.485 | 0.358 | 0.423 | 0.934 | |
| TS | 0.489 | 0.730 | 0.800 | 0.633 | 0.513 | 0.458 | 0.182 | 0.876 |

Note: Diagonals are the square root of AVE of latent variables.

4.5. Assessment and Goodness of Measurement Model

While the root mean square residual (RMSR) is a measure of the mean absolute value of the covariance residuals, the standardized root mean square residual (SRMR) based on transforming both the sample covariance matrix and the predicted covariance matrix into correlation matrices. A value less than 0.10 or of 0.08 is considered a good fit. Henseler et al. (2016) introduce the SRMR as a goodness of fit measure for PLS-SEM that can be used to avoid model misspecification. Table 3 indicates the value of SRMR, NFI and Chi-square as shown below.

Table 3
Model Fit Indices

| | Saturated Model | Estimated Model |
|------------|-----------------|-----------------|
| SRMR | 0.108 | 0.108 |
| d_ ULS | 5.400 | 5.401 |
| d_ G | 3.631 | 3.630 |
| Chi-Square | 4714.681 | 4714.829 |
| NFI | 0.468 | 0.468 |

4.6. Structural Assessment Model

Under the structural assessment model, this study assesses the coefficient of determination R2, Predictive relevance (Q2) and path coefficient and their significance to examine hypotheses of the study. The hypothesis testing is carried out using a bootstrapping technique, with a resample of the number of 5,000 bootstraps. As shown in Fig. 3, the r square values have been shown for the model.

Table 4
Path Coefficient

| Hypothesis | Paths | β | T value | P Values | Decision |
|------------|---------------------|---------|---------|----------|-------------|
| H1 | FR -> Intention | 0.001 | 0.016 | 0.988 | Unsupported |
| H2 | PA -> Intention | 0.038 | 0.482 | 0.030 | Supported |
| H3 | TMS -> Intention | 0.133 | 2.065 | 0.039 | Supported |
| H4 | IT -> Intention | 0.184 | 1.745 | 0.041 | Supported |
| H5 | TS -> Intention | 0.045 | 0.521 | 0.603 | Unsupported |
| H6 | DQ -> Intention | 0.056 | 1.006 | 0.314 | Unsupported |
| H7 | FR*IC -> Intention | -0.190 | 2.048 | 0.041 | Supported |
| H8 | PA*IC -> Intention | -0.016 | 0.226 | 0.821 | Unsupported |
| H9 | TMS*IC -> Intention | -0.058 | 0.988 | 0.323 | Unsupported |
| H10 | DQ*IC -> Intention | -0.081 | 1.082 | 0.280 | Unsupported |
| H11 | IT*IC -> Intention | 0.169 | 1.758 | 0.079 | Unsupported |
| H12 | TS*IC -> Intention | -0.086 | 0.930 | 0.353 | Unsupported |

Table 4 illustrates path coefficients (b), t statistics and p values obtained from the structural model. The results demonstrated that none of BDA enablers except TMS significantly and positively influenced intention to adopt BDA. Moreover, IC did not moderate any of BDA enablers with the intention to adopt BDA except with FR enabler. Thus, there was enough evidence to support the hypotheses H3 and H7 while all other hypotheses were rejected.

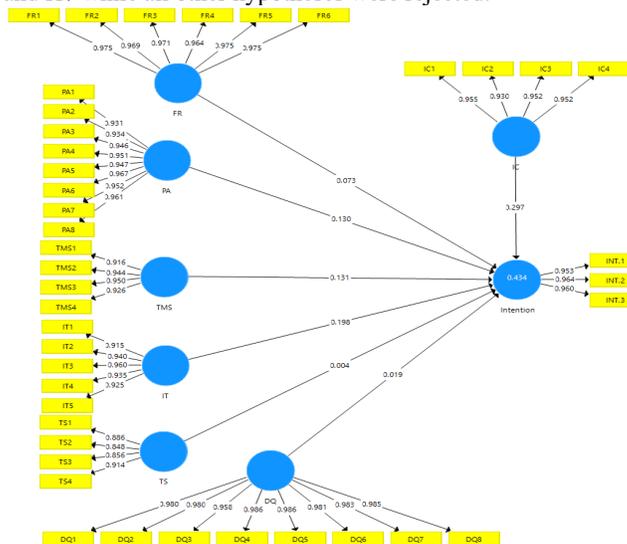


Fig. 3. Measurement assessment model

In addition, coefficient of determination is an important step in the structural model assessment (Hair et al., 2019). It indicates the total change in dependent variable happened because of independent variables. (Sarstedt et al., 2019). The range of R^2 has been prescribed from 0 to 1. Values of R^2 in between 0 to 1 shows the weak, moderate and strong variance. Table 6 shows a value of 0.478 for intention which is moderate. This shows that all intendent variables have 47.8% variance in intention as shown in Table 5.

Table 5
Coefficient of determination

| | R Square | R Square Adjusted | Decision |
|------------------|-----------------|--------------------------|-----------------|
| Intention | 0.478 | 0.444 | Medium |

Hair et al. (2019), noted that Q^2 is used to measure predictive capability of structural models. Q^2 can be calculated in PLS-SEM through the blindfolding process (Ringle et al., 2015). If the value of Q^2 is greater than zero which indicates that the path's model has predictive relevance for a particular dependent construct. As a relative measure of predictive relevance, Q^2 values of 0.02, 0.15, and 0.35, respectively, indicate that an exogenous construct has a small, medium, or considerable predictive relevance for a specific endogenous construct. Hence, as reflected in Table 6 the result of the study shows that model has considerable predictive relevance.

Table 6
The Predictive Relevance (Q^2) Effect Size

| Total | SSO | SSE | $Q^2 (=1-SSE/SSO)$ |
|------------------|------------|------------|--------------------------------------|
| Intention | 633.000 | 377.817 | 0.403 |

4.7. Discussion

The purpose of this study was to see how enabling and restricting factors affects an organization's intent to use BDA in their supply chain practices. This study highlighted critical dimensions that influence BDA adoption. Financial readiness, perceived advantages, top management support, IT infrastructure, technology sophistication, and data quality were all evaluated in this study, which was based on previous research. Moreover, the role of IC was examined as a moderator between BDA enablers and intention to use BDA.

The result of the financial readiness aspect is similar to the study done by Maduku et al. (2016), which found that financial resources had no influence on businesses' adoption of mobile technology in marketing. Therefore, this study found no significant link between financial preparedness and firms' adoption of BDA. It is possible that IT managers did not completely appreciate the benefit of BDA in SC management, resulting in underappreciated financial worries about using such a new technology. The perceived advantages of BDA and adoption intention have a favorable and substantial connection. Faced with increased competition from a wide range of businesses, organizations must examine the practical advantages that a new technology might provide prior to adopting or implementing it widely. This highly significant association between perceived advantages and desire to embrace new technological innovations is consistent with prior research of businesses' intentions to adopt new technologies (Jere & Ngidi, 2020; Tsai et al., 2010). TMS did have a direct influence on the desire to implement BDA, consistent with our hypothesis (Lai et al., 2018). This might be because companies anticipate employing BDA in SC operations anytime soon. However, as predicted by our hypothesis, IT infrastructure had a positive impact on the possibility of BDA embracing. If senior executives understand the benefits of BDA for supply chain management, they will be willing to assist in the development of the company's BDA capacity, which comprises BDA infrastructure flexibility, management skills, and staff knowledge. This research; similar to other researches; has been proven to have a significant impact on adopting business technology such as BDA (Mikalef et al., 2020; Jere & Ngidi, 2020). Our data does not support the link between technology sophistication and the plan of using BDA, which is similar to the findings of Lai et al. (2018). The non-significant link might be explained by the fact that, from our sample businesses' perspective, technology is no longer a barrier to embracing new IT innovation because they can get it through a variety of channels, including outsourcing. As for data quality, companies with high levels of quality data are potentially more likely to use BDA. The results of the finding, however, are not significant, as proven by (Lai et al., 2018). The non-significant link can be explained by the fact that traditional managers are primarily concerned with financial flow while neglecting the relevance of information availability (Rai et al., 2006). Finally, IC moderates the relationship between financial readiness and BDA intention to use, which is the only significant moderation relationship between BDA enablers and BDA intention to use. This could be because an innovation culture encourages firms to be financially prepared to implement new technology in their SC operation.

5. Conclusion

The current study's findings reveal that among six BDA enablers, three enablers including perceived advantages, top management support, and IT infrastructure, were found to have a statistically significant effect on BDA adoption intention in their SCM operations. Other variables, however, should be considered when deciding whether or not to use BDA in SCM

operations. Furthermore, the relationship between financial readiness and BDA adoption intention was significantly moderated by innovation culture. The main contribution of this article is the determination of the key challenges and obstacles to BDA process adoption in SCM context for the Consumer Goods' Retailing Sector in Jordan as a developing country. The study makes a significant contribution to both scholars and practitioners. To begin with, this study is the first to empirically examine BDA adoption in the context of SCM operations in a developing country, to our knowledge. This study gives some insights on BDA acceptability and intention to use on an organizational level by identifying possible drivers and enablers. This study has important implications for companies who are planning to adopt BDA. The empirical findings of this study highlight the need of assessing and evaluating the practical benefits BDA may offer to SC management, if not the entire organization's operation, for companies that are hesitant to utilize this new data analysis technology. Another practical input of this research is that when companies make decisions regarding new technology adoption, collaboration between various departments is required. According to our findings, managers' related responses frequently neglect the financial element when making BDA decisions, which is not the case in reality but its importance, found when it was moderated by innovation culture. BDA should not only attract TMS' interest, but many departments should embrace the chance to employ BDA to generate financial value. However, there are some limitations; instead of convenience sampling, a probability sampling approach is recommended to make the results more generalizable in the context of the study, and a larger sample size might be used. Furthermore, the study model's reliability will be enhanced by its implementation in other sectors and industries. This study model can be used in future Jordanian studies to assess the impact of BDA enablers on various levels of business performance.

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