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Unearthing the factors of big data analytics (BDA) adoption in supply chain management (SCM)

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Abstract: Technology has revolutionized business operations around the world. There is an ever-increasing trend to digitize business operations around the world. It is not uncommon to see the application of Big Data Analytics (BDA) throughout a vast range of industries and organizations in today's extremely competitive world. However, BDA adoption in supply chain (SC) is less accepted and research in this area remains at its infancy. BDA is extremely useful throughout supply chain functions like manufacturing, distribution, procurement, and marketing. However, a sizable portion of sectors continues to hold divergent opinions regarding big data's alleged benefits. Moreover, there is not a lot of empirical studies that have been published that addresses the adoption of such a tool or better yet, that investigates what factors affect the decision to adopt BDA in supply chain management (SCM). This study aims to develop and extend technology acceptance model (TAM) that considers the critical factors that may affect BDA adoption in SCM by critically analyzing the existing literature. Upon reviewing the literature, it became evident that the main categories of factors that have been thoroughly examined and recognized to be crucial in comprehending BDA adoption and acceptability in SCM are the organizational- and individual-related factors, such as top management and computer self-efficacy.

Keywords: *Acceptance model (TAM), Big data analytics, Supply Chain management, Technology*

1. Introduction

The latest development in Information and Communication Technologies (ICTs) is Big Data (BD) and Big Data Analytics (BDA). Big data (BD), which is defined by volume, variety, velocity, and value [1], is one of several technological advancements. It refers to large and complex data sets that are acquired from different sources, namely; internal and external sources. These technological sets consist of divergent data that is further computationally sorted, analyzed, and stored [2]. BDA can be divided into two components: business analytics (BA) and business analytics (BD),Wang **et al**.[3]. While the latter refers to a company's ability to use data to acquire business insights, the former lays the informational groundwork for BDA.

Big Data Analytics (BDA) is especially useful for sorting, storing, analyzing, and distributing unstructured data [2]. The application of analytics is beneficial across various organizational functions to increase productivity, make forecasts, detect future risks and optimize business processes [2]. To stay competitive, forward-thinking companies and organizations have begun to take use of big data's benefits by adding value to their operations.

BDA serves as a key source of value creation in SCM and functions as an innovation vector as well Tan et al.[4]. Big data is analyzed to obtain business intelligence insights [5], that are utilized to optimize supply chain processes, improve the management of inventory and decrease operating costs [6], ultimately increasing earnings in the supply chain industry. These BDS pioneers are aware of its potential to provide new business prospects and improve their comprehension of their industry. Nonetheless, there are still a lot of industries with differing views about the purported advantages of big

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data., despite the fact that some firms are already at the "forefront of big data analytics and are highly bullish" about its advantages and prospects.

After discovering the significant financial value BD can provide to an organization, researchers and practitioners have begun to pay enough attention to BDA as the BD era has progressed [1]. However, there is not a lot of empirical studies that have been published that addresses the adoption of such a tool or better yet, that investigates what factors affect the decision to adopt BDA in supply chain management (SCM). For instant, to test the acquisition purpose of BDA, Kwon et al. [7] suggested a model of data quality management and data usage experience. In order to investigate the relationship between TOE components and BDA adoption as well as the mechanism through which BDA influence performance, Raman et al.[8] looked at nine UK companies. Both gave insightful information on the theoretical viewpoints, however, given the features of qualitative research and case studies, it is still imperative to undertake an empirical study to examine the BDA adoption from viewpoints of supply chain management.

Despite the potential BDA offers for enhancing company performance [5], decision-making process [9], and marketing efficiency [10], the impact BDA has on supply chain management (SCM) is still unexplored. Therefore, it is better to comprehend the factors that influence BDA adoption in SCM. More specifically, this research strives to identify the individual and organizational variables that drive businesses to adopt BDA in SC

1.1. Supply Chain Management (SCM) and Big Data Analytics (BDA)

SCM is essential for retaining competitive advantage [1] as well as enhancing a company's overall business performance [3,11].

According to Mentzer **et al**. [12, pp. 4], the term "SC" designates "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, finances, and/or information from a source to a customer."

Supply chains and businesses now produce enormous amounts of data from unstructured data sources in addition to the data provided by classic transaction-based enterprise systems (such POS, RFID, and ERP) [13]. Supply chains in today's world are highly instrumented; sensors, tags, trackers, and other smart devices are gathering data in real time on a range of business activities. Cluster computing and cloud computing, two advancements in computer design, have made it easier and less expensive to store, retrieve, analyze, share, and distribute data and insights [14].

Big Data is used extensively in business and marketing, including data from social media and networking tools. Studies on the use of data and analytical capabilities for SCM (e.g., [15, 16] have generally concentrated on the use and effects of conventional data sources and analytical methods in supply chain planning and execution.

The use of Big Data in the field of SCM has also been encouraged by several scholars [17, 18].To make better decisions, SCM decision-makers must take into account all available information. In other words, according to several studies [3,19], BDA has become a strategy that creates a competitive advantage. For instance, Amazon.com uses BDA to help it accomplish 35% of sales while recommending personalized offers to customers [20].

Information sharing is paramount in SCM. When analyzing the benefits of the utilization of BD in making informed decisions, it needs to be realized that the quality of decision-making is contingent upon a number of databases obtained by the supply chain organization [21]. Additionally, competitive advantage can also mean that the company is in a more advantageous position compared to its competition. Major decisions are made with the use of highly refined information-sharing practices [22]. Organizations are becoming conscious of the benefits of BD strategies across the supply chain spectrum, from business operations all the way down to the satisfaction level of the end user [23]. The implementation of BD in operations enables top management to manage various risks and uncertainties. Although a new Delphi study revealed that there are major prospects for big data both on the supply chain level and in big corporations, it is not without its trials and perils [24].

The "5V" characteristics of BDs, according to the Gartner's lexicon, are volume, variety, velocity, value, and veracity. Thus, "volume" refers to the vast amount of data that may be gathered across the SC's various domains. Due to the constant generation of data by social interaction, monitoring tools, and various SC domains, the term "velocity" refers to how quickly digital processes can grow the amount of BD.

The term "variety" refers to the numerous types of data that are currently accessible and come from a number of dissimilar sectors of the SC, both structured and unstructured data, as well as data from outside the SC [25].

The term "Veracity" covers a wide range of concepts, including data quality and accuracy as well as correctness and sincerity [26]. The information must be correct and trustworthy. Finding relevant information that can then be converted and used is what the term "value" alludes to [27,25].

2. Literature Review

The collective outcome of factors that influence the organizational intent to adopt BDA in SCM has not been scrutinized comprehensively in the literature at the present time. There are still few empirical studies on how organizations adopt BDA and the factors that may affect their decision to adopt it [28].

Verma & Kumar, [29] looked at how system characteristics affected managers' attitudes toward using big data analytics system. In this study, a research model has been proposed based on a thorough analysis of the literature on the Technology Acceptance Model, which has been further validated by a survey of 150 big data analytics users. The survey's findings support the notion that the characteristics of big data analytics systems have a substantial direct and indirect impact on belief in the benefits of big data analytics systems and perceived usefulness, attitude and adoption. Additionally, there are mediation effects between system characteristics, big data analytics system advantages, perceived usefulness, and big data analytics system attitude.

Okcu., and Calisir, [30] conducted a study aims to investigate the variables influencing the intention to use big data tools. Job relevance, big data dimensions, compatibility, self-efficacy, complexity, and anxiety are all included in the model. An online survey was used to collect information from the company's employees for the study, which focused on a Turkish airline. 252 questionnaires in total were gathered. According to the findings, behavioral intention to use big data technologies is influenced by perceived ease of use and perceive usefulness.

The study of Alyoussef, and Al-Rahmi [31], set out to develop a methodology to quantify big data adoption in connection to education. This research used the Technology Acceptance Methodology (TAM) model to test the hypothesis that encouraging situations, perceived risk, perceived usefulness, and perceived ease of use affect students' attitudes toward use and their intention to engage in use behavior, which in turn affects the adoption of big data in education. The study used quantitative data gathering and analytic techniques to examine 282 university students. The results showed that favorable circumstances, students' attitudes about usage and behavioral intentions to use big data were significantly influenced by perceived usefulness, and perceived ease of use.

In order to investigate the use of BDA and its impact on business performance, Gangwar, [32] proposed a unified model that combines the task technology fit (TTF) and technology acceptance model (TAM) models. It also explores the organizational and environmental fit of the integrated model. 280 businesses in India's CPG & Retail, Healthcare, Banking, and Telecom were surveyed for data. The study identified perceived ease of use (PEOU) and perceived usefulness (PU) as mediating variables, and task technology fit, individual technology fit, organizational data fit, organizational process fit, and business strategy fit as important variables for affecting the use of Big Data Analytics.

Brock & Khan, [33] integrating Technology Acceptance Model (TAM) with the Organizational Learning Capabilities (OLC) framework, this research attempts to examine the factors related with the use of big data analytics. These models are applied to the construct, intended usage of big data and the mediation effect of the OLC constructs is assessed. Students at the University of Liverpool who are majoring in information technology subjects provide the study's data.

Lai & Ren [34] used Technological, Organizational, and Environmental framework (TOE) to examine the factors influencing a firm's intention to implement BDA in its daily operations. This study specifically divides potential components into the following four groups: technology, organizational, environmental, and SC characteristics. The empirical findings showed that top management support and perceived benefits might have a big impact on adoption intention. Additionally, the direct linkages between the driving motivations and the intention to adopt can be greatly moderated by environmental factors like the adoption of competitors, governmental regulations, and SC connectivity.

Alaskar et al. [35] used Technological, Organizational, and Environmental framework (TOE) to determine the primary factors of Saudi Arabian enterprises' intention to use Big Data Analytics (BDA) in supply chain management (SCM). The goal of this study is to determine and examine how competitive pressure functions as a contextual variable that can mitigate the impact of these variables on the intention to adopt. The empirical findings showed that compatibility, relative benefit, and top management support are positively affect the firms' intention to adopt BDA in SCM.

In order to investigate the affect of BDA on value creation in SCM, Chen **et al**. [1] use the technology, organization, and environment (TOE) model to determine and theorize the mechanisms through which various factors impact BDA adoption in practice. The study was based on survey data gathered from 161 U.S.-based companies. The finding reveals that organizational and environmental factors directly influence organizational BDA usage and top management support plays an indirect role in influencing organizational BDA usage.

Agrawal and Madaan, [36] examined the barriers to big data (BD) adoption in the healthcare supply chain (HSC). EFA was utilized in the division of 13 barriers into three groups: "data governance perspective," "technological and expertise perspective," and "organizational and social perspective." Three hypotheses were examined, and each has found to be significant. According to the study's findings, the elements of "technological and expertise perspective" and "organizational and social perspective" have a positive relationship with the "data governance perspective." The "organizational and social perspective" and the "technological and expertise perspective" are also strongly correlated.

Lamba and Singh, [37] examined the relationships between the several enablers that are essential to the success of big data projects in operations supply chain management (OSCM). Driving enablers have been identified using three different multicriteria decision-making (MCDM) techniques: fuzzy total interpretive structural modeling (fuzzy-TISM), interpretive structural modeling (ISM), and decision-making trial and evaluation laboratory (DEMATEL). The findings of the research showed that the most significant/driving enablers include top management commitment, funding for big data projects, big data/data science skills, organizational structure, and change management programs.

Every study that has been cited focuses on the organizational perspective of innovation adoption. From these suppositions, it emerges that several models, including BD, have been proposed to examine how the technologies may be adopted by businesses. Still lacking, though, is a novel perspective that uses the SC and BDA rather than an organization as the analytical unit. This is ascertained in the BDA literature showing the limited exploration of BDA adoption more specifically in SC. Therefore, this research will focus on the adoption stage of the BDA with the aim to develop a theoretical model that will be used when determining the BDA adoption in supply chain.

3. Theoretical Framework

The understanding of user acceptability of information technology has been the subject of numerous research project. Examining user adoption of a technology has made extensive use of numerous well-established frameworks, theories, and theoretical models. The technology acceptance model (TAM) [38] is the most widely used to discuss the acceptance and use of a technology, as shown in Figure 1, and has governed the theoretical basis of information technology acceptance for the past 20 years [39,40].

TAM's objective, according to Davis [38], is to provide a foundation for evaluating how internal beliefs, attitudes and the intention of using technological gadgets (such as computers) is affected by external factors. As illustrated in Figure 1, the TAM model hypothesises that two specific beliefs – Perceive Usefulness (PU) and Perceive Ease of Use (PEOU) – are of the utmost significance in the determination of computer acceptance behaviours. Davis [38, pp, 26] explains PU as "the degree to which an individual believes that using a particular system would enhance his or her job performance". PEOU – as explained by Davis [38, pp.82] – is "the degree to which an individual believes that using a particular system would be free of physical and mental effort".

Different research studies have employed this framework and have evidenced the usability of this framework in assessing the organizational commitment towards adopting technology [41], Such as in e-commerce [42], cloud ERP [43,44], cloud computing [45,46], BDA [47, 48, 49, 50].

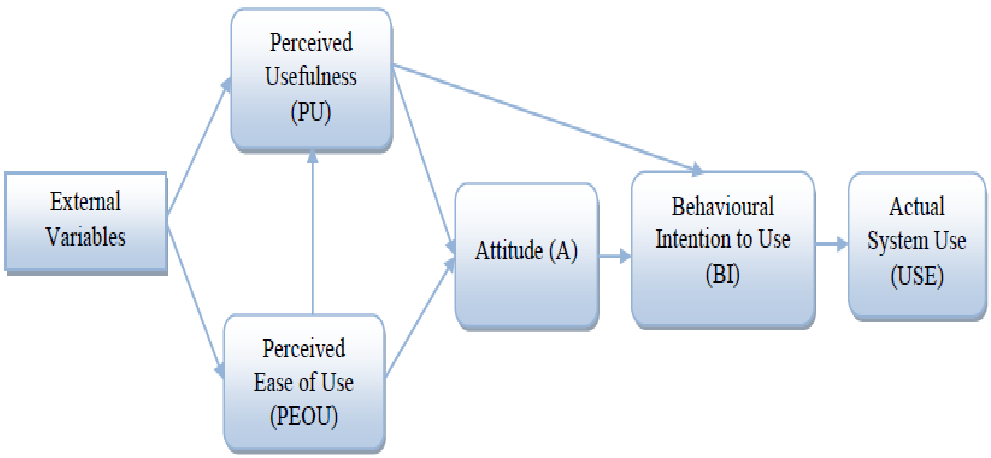

Figure 1.
Technology acceptance model (TAM).
Source: Davis et al. [38].

The majority of previous research studies utilized the Technology–Organization–Environment (TOE) to identify the factors that may affect BDA adoption. Some may wonder why not utilize TOE model instead of using TAM. Despite this model has been used to develop frameworks and conceptual models in order to understand the relationship of various factors that may affect technology adoption, it is worth noting that the previous research on TOE model have not been empirically proven [51]. Different research studies [52, 53, 54] examined the adoption of IS by the use of a TOE framework. However, some studies based on this framework have several limitations [55]. For example, Low et al. [46] indicated that TOE framework's lack major constructs and that variables of TOE frameworks may differ from one context to another [56]. Thus, TOE frameworks should include other variables – such as sociological and cognitive variables – to enrich them [57,58]. Dedrick and West [59], argued that the TOE framework is only concerned with variables classifications and the framework cannot be considered as a well-developed theory because it does not act as an integrated conceptual framework. The TOE framework has been integrated with other technology acceptance frameworks that have clear constructs and, more particularly, with TAM. However, integrating TOE and TAM raises concerns relating to the variables of the two models. First, TAM has many external variables that have been identified and examined by different research studies, whereas TOE's variables differ from one research study to another and are not widely accepted [55]. Second, the significance of the variables for both frameworks differs from one country to another and from one technology to another. Some variables could be found to be consistently insignificant in a group of contexts or studies [55].

Concerns have also been raised about the voluntary approach to technology use as opposed to the mandatory use. It is impossible to ignore the significance of this mandatory use, especially when it comes to well-known technologies like enterprise resource planning (ERP) and collaboration suites.

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However, less widely used and regulated technologies and processes, such as big data analytics, still heavily rely on voluntary usage.

TAM adoption has come under fire since it just offers a broad framework and offers no specific direction. In an effort to identify boundary conditions, several researchers tried to expand the TAM model with additional variables and investigate their impact on PEOU and PU. Agarwal and Prasad [60] utilized five individual factors (e.g., training, prior experiences, job position, level of education, and role with reference to technology). Three organizational factors, such as computer support, top management support, and train were employed by Igbaria **et al.** [61] as external determinants of PEOU and PU. The causes of PEOU and PU were divided into individual, organizational, and technology variables by Sternad **et al**. [62].

Because PU and PEOU in the TAM framework might not accurately reflect users' intentions to embrace information systems (IS), researchers should look into how additional factors affect user acceptability in addition to the perceive ease of use and usefulness of IS [63].

TAM presents a framework through which the effects of external factors on the usage of a system can be investigated [64]. In this local, this research will explore the external factors that may affect the adoption of BDA in SCM. By extending the TAM model in a new domain, this research study may lead to contemporary research strands of BDA implementation theory and adoption.

4. Research Model Development

Companies and enterprises differ in terms of their organizational structure and business operations. Given that different departments operate independently and have different user needs in a health environment, organizational and individual issues may be important and require particular consideration. Bremser (65,pp.12) stated "Organizational aspects, such as unclear processes, lack of analytical skills or indistinct prioritization of use cases are further obstacles to the successful adoption of big data". According to Helo et al. [66] and Venkatesh [67], the primary problems with IS are organizational and individual-related rather than technological, such complexity, compatibility, and standardization. Technology adoption is not entirely dependent on the technical aspects of IT. External aspects – such as organisational and individual characteristics – are also important in order to facilitate adoption [68]. Based on the above discussion, two main categories of variables have been adopted in this research. The first category is organisational factors, such as top management support and user training. The second category is individual factors, such as subjective norm, computer self-efficacy and computer anxiety. These external factors (both organisational and individual) have been validated in different empirical studies, including research relating to BDA adoption, and have strong support in the literature. However, despite the wide recognition of these factors in previous models, the majority – if not all – of prior research studies have failed to apply them in a single model in order to understand their influences on BDA adoption in SCM.

4.1. Organizational Factors

User Training: Numerous prior studies [69, 70,71] on the adoption of IT and IS in different industries highlight the critical role that user training plays in the effective application of IT packages. The success of IT installation is said to be mostly determined and influenced by user education and training. This is due to the fact that user education and training aid in both the process of organizational change and the adaptation of new IT systems [72]. Effective training is an essential factor in encouraging users to have a favorable attitude toward the system [73]. Insufficient training for IT users' decreases ease of use of the technology and hence makes users more resistant, which can have a significant negative impact on IT success and usage [71].

According to Ruivo et al. [74], when users have a good understanding of the system because they are endowed with an adequate training programme, such training improves users' perceptions with regard how easy is to use the system.

Top Management Support: Many researchers have recognized the significance of top management support for the successful adoption and acceptance of IT [75,76], particularly when the outcomes are dynamic and unpredictable. Liang et al. [77] assert that senior management exercises strong leadership in order to assist staff members in dispelling any lingering issues regarding the usage of technology. Prior research has demonstrated that top management support improves user performance and attitude, particularly when implementing new technologies. Top management support and perceive usefulness are important factors affecting the adoption of big data [3]. Users' attitudes are improved by that top management support, which also lowers computer anxiety [78]. that top management support is critical factor for perceive ease of use and perceive usefulness [79,80].

4.2. Individual Factors

Self-efficacy: refers to the belief that one can carry out a specific task or that one can carry out an activity successfully [81]. Computer self-efficacy is a term that is recognized and defined in the context of adopting information technologies and systems as a judgment of one's capability to use a computer. Kwahk and Ahn [82,pp.187] stated that: "when individuals believe that they will be able to use computers and IT with great skill, they are more likely to expect beneficial outcomes from using computers and IT compared to when they doubt their computer related-capabilities". According to Venkatesh and Davis [83], when implementing new technologies, a key factor of adoption and implementation success is computer self-efficacy. These studies have shown that self-efficacy is a predictor of perceived ease of use (PEOU) and establishes a person's attitude for using specific technological instruments. It is also an important antecedent of the perceived usefulness of the technologies adopted. In conclusion, user perceptions of IT ease of use and consequently its usefulness are influenced by computer self-efficacy.

Subjective Norms: A person's view of what the majority of significant others believe about whether or not they should engage in a particular conduct can be characterized as subjective norms. When early TAM researchers realized that there were no meaningful findings supporting the idea that subjective norms had a substantial impact on perceived usefulness when adopting new information technologies, they abandoned subjective norms as a study subject. However, other research studies have validated the use of subjective norms to assess perceived usefulness to the greatest degree, especially in situations when users have little familiarity with the technology in question. Melone [84] and Hartwick and Barki [85], suggested that subjective norm may positively and significantly influence perceive usefulness and the intention to adopt technologies.

Computer Anxiety: It has been demonstrated that computer anxiety causes people to avoid computers, and it is a phobic condition that may be treated, making research on computer anxiety essential [86]. Computer anxiety is defined by Shu and Wang [87] as a person's incapacity to manage the rapidly changing ICT usage patterns in both the social and professional spheres. Shih and Huang (80,pp.267) stated that "individuals with lower anxiety are much more likely to interact with computers than people with higher anxiety".According to earlier studies, computer anxiety facilitates the intention to use IT [89,86]. Computer anxiety affects both the PEOU of IT and the intention to use it [89, 90]. Additionally in favor of this, Brown [91], who claim that Technology anxiety had a significant affect on PEOU.

4.3. SC Connectivity

Considering the aim of this research is to examine the firm's intention to adopt BDA in SCM, It is vital and essential to consider the SC characteristics into account. In simple terms, SC connectivity refers to the company's ability to quickly utilize "communication and information technology" to provide the data required to make decisions and accomplish goals. Essentially, the SC connectivity is about connecting SC with relevant data and technology. Fawcett et al., [91, pp. 3] defined SC connectivity as "the ability of a firm to use IT to collect, analyze and disseminate information needed to synchronize decision-making across value-added activities". The main predictor for the BDA ability is

SC connectivity. The development of the big data analytics capability occurs when the SC connectivity improves because at that point, the company has access to large datasets and information, as well as connectivity, which can help the company's big data analysis capabilities. The advantages that BDA may provide for businesses are the primary driver behind its adoption in SCM. The presence of a higher-degree of SC connectivity will further improve the relationship between using BDA and the intention to adopt BDA [92]. According to Alaskar **et al**. [93], SC connectivity positively moderates the link between top management support and intention to adopt BDA.

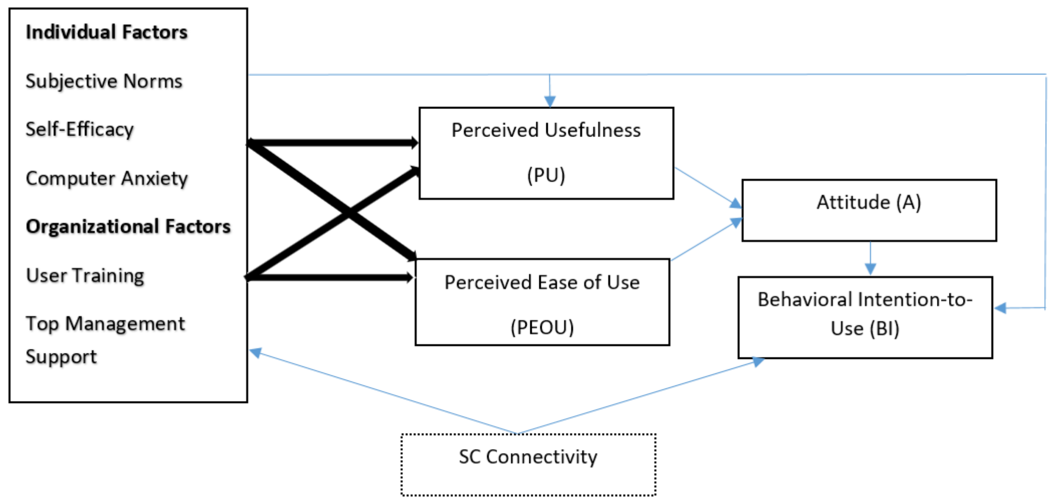

Figure 3.

5. Conclusion

The examination of the literature conducted for this study highlights some of the gaps in the body of knowledge regarding BDA Adoption. This is especially true given the paucity of research on the adoption of BDA in SCM environments and the relatively small amount of research that focuses on the BDA adoption stage and offers precise guidelines for the adoption and implementation of BDA in SCM. Examining the literature made it evident that there were two primary categories of variables that had been investigated and demonstrated to be significant in explaining technology acceptance: organizational factors (user training and top management support) and individual factors and information literacy (such as computer self-efficacy and subjective norm). A conceptual framework for BDA adoption in SCM has been developed by combining the identified factors into a single model, which is based on the TAM model and the literature research on BDA. In order to address the BDA adoption and acceptance decisions, this research has established a new extended technology acceptance model through a review of the current literature. This research has two primary limitations. First, the research is limited by the small number of literature sources that are available in the particular field of study; second, the conceptual research model that has been established only includes only two categories of factors. In order to validate the created research model, the empirical study will be the focus of future research. Research using quantitative methods can be utilized to investigate the relationships among the model's variables. The goal of the research is to gather data from several organizations that have the intention to adopt BDA in their supply chains.

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References

[1] 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.

[2] Gangwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. Information Resources Management Journal (IRMJ), 31(4), 1-22. doi:10.4018/IRMJ.2018100101

[3] Wang, L., Yang, M., Pathan, Z. H., Salam, S., Shahzad, K., & Zeng, J. (2018). Analysis of influencing factors of big data adoption in Chinese enterprises using DANP technique. *Sustainability*, *10*(11), 3956.

[4] Tan, K. H., & Zhan, Y. (2017). Improving new product development using big data: a case study of an electronics company. *R&D Management*, *47*(4), 570-582.

[5] Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234-246.

[6] Christopher, M., & Ryals, L. J. (2014). The supply chain becomes the demand chain. *Journal of Business Logistics*, *35*(1), 29-35

[7] 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.

[8] Raman, S., Patwa, N., Niranjan, I., Ranjan, U., Moorthy, K., & Mehta, A. (2018). Impact of big data on supply chain management. *International Journal of Logistics Research and Applications*, *21*(6), 579-596. https://doi.org/10.1080/13675567.2018.1459523

[9] Janssen, M., Van Der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of business research*, *70*, 338-345.

[10] Xu, F., Lin, Y., Huang, J., Wu, D., Shi, H., Song, J., & Li, Y. (2016). Big data driven mobile traffic understanding and forecasting: A time series approach. *IEEE transactions on services computing*, *9*(5), 796-805.

[11] 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.

[12] Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business logistics*, *22*(2), 1-25.

[13] Zhong, R. Y., Huang, G. Q., Lan, S., Dai, Q. Y., Chen, X., & Zhang, T. (2015). A big data approach for logistics trajectory discovery from RFID-enabled production data. *International Journal of Production Economics*, *165*, 260-272. https://doi.org/10.1016/j.ijpe.2015.02.01

[14] Sanders, N. R., & Ganeshan, R. (2018). Big data in supply chain management. *Production and Operations Management*, *27*(10), 1745-1748.

[15] Olson, E. L. (2013). It's not easy being green: the effects of attribute tradeoffs on green product preference and choice. *Journal of the Academy of Marketing Science*, *41*, 171-184.

[16] Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80.

[17] Huang, X., & Du, X. (2014, April). Achieving big data privacy via hybrid cloud. In *2014 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)* (pp. 512-517). IEEE.

[18] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business logistics*, *34*(2), 77-84.

[19] Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of business research*, *70*, 263-286.

[20] Wills, M. J. (2014). Decisions through data: Analytics in healthcare. *Journal of Healthcare Management*, *59*(4), 254-262.

[21] Janssen, S. J., Porter, C. H., Moore, A. D., Athanasiadis, I. N., Foster, I., Jones, J. W., & Antle, J. M. (2017). Towards a new generation of agricultural system data, models and knowledge products: Information and communication technology. *Agricultural systems*, *155*, 200-212.

[22] Wood, L. C., Reiners, T., & Srivastava, H. S. (2017). Think exogenous to excel: alternative supply chain data to improve transparency and decisions. *International Journal of Logistics Research and Applications*, *20*(5), 426-443.

[23] Buganza, T., Trabucchi, D., & Pellizzoni, E. (2020). Limitless personalization: the role of Bi Data in unveiling service opportunities. *Technology analysis & strategic management*, *32*(1), 58-70.

[24] Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International journal*

[25] Xu, L. D., & Duan, L. (2019). Big data for cyber physical systems in industry 4.0: a survey. *Enterprise Information Systems*, *13*(2), 148-169.

[26] Saha, B., & Srivastava, D. (2014, March). Data quality: The other face of big data. In *2014 IEEE 30th international conference on data engineering* (pp. 1294-1297). IEEE.

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[27] Makris, D., Hansen, Z. N. L., & Khan, O. (2019, April). Adapting to supply chain 4.0: an explorative study of multinational companies. In *Supply Chain Forum: An International Journal* (Vol. 20, No. 2, pp. 116-131). Taylor & Francis.

[28] Kshetri, N. (2014). The emerging role of Big Data in key development issues: Opportunities, challenges, and concerns. *Big Data & Society*, *1*(2), 2053951714564227.

[29] Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing & Management*, *54*(5), 791-806.

[30] Okcu, S., Hancerliogullari Koksalmis, G., Basak, E., & Calisir, F. (2019). Factors affecting intention to use big data tools: an extended technology acceptance model. In *Industrial Engineering in the Big Data Era: Selected Papers from the Global Joint Conference on Industrial Engineering and Its Application Areas, GJCIE 2018, June 21–22, 2018, Nevsehir, Turkey* (pp. 401-416). Springer International Publishing.

[31] Alyoussef, I. Y., & Al-Rahmi, W. M. (2022). Big data analytics adoption via lenses of Technology Acceptance Model: empirical study of higher education. *Entrepreneurship and Sustainability Issues*, *9*(3), 399

[32] Gangwar, H. (2020). Big Data Analytics Usage and Business Performance: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model. *Electronic Journal of Information Systems Evaluation*, *23*(1), pp45-64.

[33] Brock, V., & Khan, H. U. (2017). Big data analytics: does organizational factor matters impact technology acceptance?. *Journal of Big Data*, *4*, 1-28.

[34] 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. *The International Journal of Logistics Management*. https://doi.org/10.1108/IJLM-06-2017-

[35] Alaskar, T. H., Mezghani, K., & Alsadi, A. K. (2021). Examining the adoption of Big data analytics in supply chain management under competitive pressure: evidence from Saudi Arabia. *Journal of Decision Systems*, *30*(2-3), 300-320.

[36] Agarwal, R. and Prasad, J. (1999) Are Individual Differences Germane to the Acceptance of New Information Technologies? Decision Sciences, 30(2), pp. 361-91. https://doi.org/ 10.1111/j.1540-5915.1999.tb01614.x

[37] Lamba, K., & Singh, S. P. (2018). Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management*, *29*(2), 629-658.

[38] Davis, F D. (1986) A Technology Acceptance Model for Empirically Testing New Enduser Information Systems: Theory and Results. Doctoral dissertation. Sloan School of Management, Massachusetts Institute of Technology

[39] Kim, S.S. and Malhotra, N.K. (2005) A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. Management science, 51(5), pp.741-755. https://doi.org/10.1287/mnsc.1040.0326

[40] Adams, D.A., Nelson, R.R. and Todd, P.A. (1992) Perceived Usefulness, Ease of Use, and Usage of Information. MIS Quarterly, 16(2), pp. 227-247. https://doi.org/10.2307/249577

[41] Hong, W., & Zhu, K. (2006). Migrating to internet-based e-commerce: Factors affecting e-commerce adoption and migration at the firm level. *Information & Management*, *43*(2), 204–221. https://doi. org/10.1016/j.im.2005.06.003

[42] Oliveira, T., & Martins, M.F. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems*, *110*(9), 1337–1354. https://doi.org/10.1108/ 02635571011087428

[43] Awa, H.O., & Ojiabo, O.U. (2016). A model of adoption determinants of ERP within TOE framework. Information Technology & People., 29(4), 901–930. https://doi.org/10.1108/ITP-03-2015-0068

[44] Usman, M. J., Ismail, A. S., Abdul-Salaam, G., Chizari, H., Kaiwartya, O., Gital, A. Y., ... & Dishing, S. I. (2019). Energy-efficient nature-inspired techniques in cloud computing

[45] 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.

[46] Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial management & data systems*, *111*(7), 1006-1023.

[47] Agrawal, K. (2015). Investigating the determinants of Big data analytics (BDA) adoption in Asian emerging economies. *Proceedings of the Americas Conference on Information Systems*. AMC'S. https://doi.org/10.5465/AMBPP.2015.11290abstract

[48] 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. *The International Journal of Logistics Management*. https://doi.org/10.1108/IJLM-06-2017-

[49] Ennouri, M. F., & Mezghani, K. (2021). Big data management in the era of FinTech: insights from a literature review. *Influence of FinTech on Management Transformation*, 102-120.

[50] Verma, S., & Chaurasia, S. (2019). Understanding the determinants of Big data analytics adoption. *Information Resources Management Journal (IRMJ)*, *32*(3), 1–26. https://doi.org/10.4018/IRMJ. 2019070101

[51] Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information systems research*, *8*(3), 240-253.

[52] Pan, M. J., & Jang, W. Y. (2008). Determinants of the adoption of enterprise resource planning within the technology-organization-environment framework: Taiwan's communications industry. *Journal of Computer information systems*, *48*(3), 94-102.

[53] Kouki, R., Poulin, D., & Pellerin, R. (2010). The impact of contextual factors on ERP assimilation: Exploratory findings from a developed and a developing country. *Journal of global information technology management*, *13*(1), 28-55.
[54] Ramdani, B., Kawalek, P., & Lorenzo, O. (2009). Predicting SMEs' adoption of enterprise systems. *Journal of enterprise information management*, *22*(1/2), 10-24.
[55] Gangwar, H., Date, H., & Raoot, A. D. (2014). Review on IT adoption: insights from recent technologies. *Journal of enterprise information management*, *27*(4), 488-502.
[56] Wang, L., Yang, M., Pathan, Z. H., Salam, S., Shahzad, K., & Zeng, J. (2018). Analysis of influencing factors of big data adoption in Chinese enterprises using DANP technique. *Sustainability*, *10*(11), 3956.
[57] Jang, H., Reeve, J., & Deci, E. L. (2010). Engaging students in learning activities: It is not autonomy support or structure but autonomy support and structure. *Journal of educational psychology*, *102*(3), 588.
[58] Wen, K. W., & Chen, Y. (2010). E-business value creation in Small and Medium Enterprises: a US study using the TOE framework. *International Journal of Electronic Business*, *8*(1), 80-100.
[59] Dedrick, J., & West, J. (2003, December). Why firms adopt open source platforms: a grounded theory of innovation and standards adoption. In *Proceedings of the workshop on standard making: A critical research frontier for information systems* (pp. 236-257).
[60] Agarwal, R. and Prasad, J. (1999) Are Individual Differences Germane to the Acceptance of New Information Technologies? Decision Sciences, 30(2), pp. 361-91. https://doi.org/ 10.1111/j.1540-5915.1999.tb01614.x
[61] Igbaria, M., Guimaraes, T., & Davis, G. B. (1995). Testing the determinants of microcomputer usage via a structural equation model. *Journal of management information systems*, *11*(4), 87-114.
[62] Sternad, S., Gradisar, M. and Bobek, S. (2011) The Influence of External Factors on Routine ERP Usage. Industrial Management & Data Systems, 111(9), pp. 1511-1530. https://doi.org/10.1108/02635571111182818
[63] Mathieson, K. (1991) Predicting User Intentions: Comparing the Technology Acceptance Model with Theory of Planned Behavior. Information Systems Research, 2(3), p. 173. https://doi.org/10.1287/isre.2.3.173
[64] Hong, H., Qiu, J., & Liang, Y. (2010). Environmental factors influencing the distribution of total and fecal coliform bacteria in six water storage reservoirs in the Pearl River Delta Region, China. *Journal of Environmental Sciences*, *22*(5), 663-668.
[65] Bremser, C. (2018). Starting points for big data adoption.
[66] Helo, P., Anussornnitisarn, P. and Phusavat, K. (2008) Expectation and Reality in ERP Implementation: Consultant and Solution Provider Perspective. Industrial Management & Data Systems, 108(8), pp. 1045-1059. https://doi.org/10.1108/02635570810904604
[67] Venkatesh, V. and Davis, F. (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), pp. 186- 204. https://doi.org/10.1287/mnsc.46.2.186.11926
[68] Orlikowski, W. and Baroudi, J. (1991) Studying Information Technology in Organizations: Research Approaches and Assumptions. Information Systems Research, 2(1), pp. 1-28.
[69] Bradley, J., & Lee, C. C. (2007). ERP training and user satisfaction: A case study. *International Journal of Enterprise Information Systems (IJEIS)*, *3*(4), 33-50.
[70] Koh, S., Gunasekaran, A., & Cooper, J. (2009). The demand for training and consultancy investment in SME-specific ERP systems implementation and operation. International Journal of Production Economics, 122(1), 241-254.
[71] Kale, V. (2000) Implementing SAP r/3. Indianopolis, SAMS.
[72] Zornada, M. (2005). E-learning and the changing face of corporate training and development. *Managing global transitions*, *3*(1), 5-21.
[73] Choi, D.H., Kim, J. and Kim, S.H. (2007) ERP Training with a Web-based Electronic Learning System: The Flow Theory Perspective. *International Journal of Human-Computer Studies*, 65(3), pp. 223-243
[74] Ruivo, P., Oliveira, T., & Neto, M. (2014). Examine ERP post-implementation stages of use and value: Empirical evidence from Portuguese SMEs. *International journal of accounting information systems*, *15*(2), 166-184.
[75] Majid, S., Foo, S., Luyt, B., Zhang, X., Theng, Y. L., Chang, Y. K., & Mokhtar, I. A. (2011). Adopting evidence-based practice in clinical decision making: nurses' perceptions, knowledge, and barriers. *Journal of the Medical Library Association: JMLA*, *99*(3), 229.
[76] Woo, H.S. (2007) Critical Success Factors for Implementing ERP: The Case of a Chinese Electronic Manufacturer. *Journal of Manufacturing Technology*, 18(4), pp. 431-442.
[77] Liang, H., Saraf, N., Hu, Q. and Xue, Y. (2007) Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly*, pp. 59-87
[78] Igbaria, M. and Chakrabarti, A. (1990) Computer anxiety and attitudes towards microcomputer use. Behaviour & Information Technology, 9(3), pp.229-241. https://doi. org/10.1080/01449299008924 23
[79] Lee, D., Lee, S.M., Olson, D.L. and Hwan Chung, S. (2010) The Effect of Organizational Support on ERP Implementation. *Industrial Management & Data Systems*, 110(2), pp. 269-283
[80] Shih, Y.Y., Huang, S.S. (2009) The Actual Usage of ERP Systems: An Extended Technology Acceptance Perspective. *Journal of Research and Practice in Information Technology*, 41(3), pp. 263-276
[81] Bandura, A. and Wessels, S. (1997) *Self-efficacy* (pp. 4-6). W.H. Freeman & Company
[82] Kwahk, K.Y. and Ahn, H. (2010) Moderating Effects of Localization Differences on ERP Use: A Socio-technical Systems Perspective. *Computers in Human Behavior*, 26(2), pp. 186-198.

[83] Venkatesh, V. and Davis, F. (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), pp. 186- 204. https://doi.org/10.1287/mnsc.46.2.186.11926
[84] Melone, N. P. (1990). A theoretical assessment of the user-satisfaction construct in information systems research. *Management science*, *36*(1), 76-91
[85] Hartwick, J., & Barki, H. (1994). Explaining the role of user participation in information system use. *Management science*, *40*(4), 440-465.
[86] Olatoye, R. (2011) Levels of Participation in ICT Training Programmes, Computer Anxiety and ICT Utilization Among Selected Professionals. *International Journal of Education and Development using ICT*, 7(2), pp. 15-26.
[87] Shu, Q., Tu, Q. and Wang, K. (2011) The Impact of Computer Self-efficacy and Technology Dependence on Computer-related Technostress: A Social Cognitive Theory Perspective. *International Journal of Human-Computer Interaction*, 27(10), pp. 923-939
[88] Phang, C.W., Sutanto, J., Kankanhalli, A., Li, Y., Tan, B.C. and Teo, H.H. (2006) Senior Citizens' Acceptance of Information Systems: A Study in the Context of E-government Services. *IEEE Transactions on Engineering Management*, 53(4), pp. 555-569.
[89] Venkatesh, V. and Bala, H. (2008) Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, 39(2), pp. 273-315
[90] Brown, I. T. (2002). Individual and technological factors affecting perceived ease of use of web-based learning technologies in a developing country. *The Electronic Journal of Information Systems in Developing Countries*, *9*(1), 1-15.
[91] 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. *Journal of supply chain management*, *47*(1), 38-59.
[92] 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. *The International Journal of Logistics Management*. https://doi.org/10.1108/IJLM-06-2017-
[93] Alaskar, T. H., Mezghani, K., & Alsadi, A. K. (2021). Examining the adoption of Big data analytics in supply chain management under competitive pressure: evidence from Saudi Arabia. *Journal of Decision Systems*, *30*(2-3), 300-320.