Technological Forecasting & Social Change 169 (2021) 120808

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

The role of big data analytics capabilities in greening e-procurement: A higher order PLS-SEM analysis

Bader Khamis AlNuaimi, Conceptualization; Theoretical Background; Data Collection; Analysis and Writeup [a], Mehmood Khan, Conceptualization; Review of Analysis and Writeup [a,*], Mian M. Ajmal, Conceptualization and Theoretical Background [a]

[a] College of Business, Abu Dhabi University, P.O. Box 59911, Abu Dhabi, UAE

ARTICLE INFO

Keywords:
Big data
Green procurement
resource orchestration
sustainable development
United Arab Emirates

ABSTRACT

The emergence of big data technology and concepts has created the potential to transform and innovate the traditional e-procurement system into green e-procurement. Utilizing resource orchestration theory, this paper suggests that if organizations embrace and reorganize some of the resources and capabilities offered by big data within their e-procurement functions, it will help achieve improved environmental performance. Based on a sample of 216 procurement professionals in the United Arab Emirates, we empirically investigate the effects of big data analytics capabilities (BDAC) on e-procurement (EP) and environmental performance (ENP) using PLS-SEM analysis. This paper has determined that EP does not influence (ENP), but it has a significant influence on BDAC; and when BDAC was introduced as a mediator between EP and ENP, a significant and positive effect was found on ENP, indicating full mediation. Our findings offer a more advanced understanding of the impact of BDAC on e-procurement, thereby addressing the crucial questions of how and when BDAC can enhance environmental sustainability in procurement and supply chains.

1. Introduction

1.1. Background

Implementing green procurement (GP) in any organization is necessary to achieve higher environmental performance (ENP), yet it is an extremely challenging task. It is unrealistic to expect officers, managers, and procurers to adopt environmentally-friendly procurement practices in the absence of the appropriate information, tools, and training on the concept of lifecycle costs (Darnall *et al.*, 2008). Thus, there are increasing calls to use IT-based procurement systems such as e-procurement (EP) to improve ENP (Allal-Chérif, 2010; Raghavendran *et al.*, 2012; Ramkumar and Jenamani, 2015). However, implementing GP in EP platforms goes beyond merely transferring GP procedures to EP tools. Instead, it requires restructuring various pre-award and post-award phases and integrating ENP data and feedback, making these processes simpler and making GP more manageable (Muñoz-Garcia and Vila, 2018). Furthermore, there are many types of EP platforms, and not all of them provide the flexibility required for the efficient integration of GP. As reported, many procurement decisions rarely incorporate actual and up-to-date field data and performance feedback relating to the procured parts and the inherent life cycle of products. The limitations of traditionally available EP platforms often result in the acquired information not being used (Chidambaram *et al.*, 2015). Thus, it was suggested that the next set of improvements in EP systems should be allowing the integration of operational data and the adoption of big data capabilities and data-driven mindset (Chidambaram *et al.*, 2015; Ruehle, 2018).

By leveraging big data concepts, procurement functions can quickly gather more information and collaborate with other organization functions to make more informed GP decisions across the product life cycle (Chidambaram *et al.*, 2015). As a result of this potential, digitization and data integration are considered an integral approach to preserving the environment and achieving the sustainable exploitation of natural resources (Wu, J. *et al.*, 2018). That is why there have been increasing demands for more big data to secure a sustainable future (Dubey *et al.*, 2017; Griggs *et al.*, 2013).

Yet, during the "Big Data" and "Industry 4.0" revolutions of recent years, organizations have increasingly looked to technologies such as cloud computing, blockchain, and big data analytics (BDA), to renovate

* Corresponding Author.
E-mail addresses: 1063826@students.adu.ac.ae (B.K. AlNuaimi), mehmood.khan@adu.ac.ae (M. Khan), mian.ajmal@adu.ac.ae (M.M. Ajmal).

https://doi.org/10.1016/j.techfore.2021.120808
Received 1 November 2020; Received in revised form 1 April 2021; Accepted 10 April 2021
Available online 11 May 2021

everything from marketing and sales to supply chain management, while ignoring the procurement function, as organizations tend to retain outdated procurement processes and technologies (Ruehle, 2018). In fact, the available literature on BDA suggests that the public sector remains less studied than the private sector (Choi *et al.*, 2018; Manikam *et al.*, 2017), and IT-based procurement have rarely been investigated in the context of GP and environmental performance (Chersan *et al.*, 2020). Moreover, Ma *et al.* (2019) concluded that there is a need for additional research on AI and IoT in the public sector. They called for greater involvement of practitioners in studies of this nature because they likely have a more in-depth and more complete view of which elements are related to BDA and the public sector, which is this paper's aim.

1.2. Purpose and significance

Although big data technology has become more available for organizations, big data can be of limited value if decision-makers and employees within an organization cannot understand big data analysis (Labrinidis and Jagadish, 2012). Nevertheless, recent studies suggest that almost every organization already has the necessary resources and capabilities to implement BDA in their procurement function, and transforming from heuristic approximations to data-driven analytics can be achieved in a few months with targeted efforts in three key areas: (1) people, (2) process, and (3) technology (Innamorato *et al.*, 2017; Mikalef *et al.*, 2019a). Consequently, this paper suggests that if organizations embrace and reorganize some of the resources and capabilities offered by big data within their EP functions, it will help achieve higher ENP. Drawing upon this and utilizing the resource orchestration theory (ROT), the purpose of this paper was threefold: (1) to examine the relationships between EP and ENP; (2) to investigate the relationship between EP and big data analytics capabilities (BDAC); and (3) to identify what, if any, direct and indirect effects of BDAC have on the relationship between EP and ENP.

Furthermore, this paper recognizes that the concepts of GP and big data are relatively new in the United Arab Emirates (UAE), so knowledge and experience in this area are possibly lacking. However, the paper is based on a quantitative survey to measure EP, ENP, and some of the BDAC in UAE organizations who have already adopted business intelligence practices and BDA in their procurement function or considering taking business intelligence. Purposive sampling was used, and 216 valid samples were obtained. We sought to offer new evidence to highlight the importance of utilizing BDAC to achieve higher ENP via EP. Specifically, BDAC has the potential to become a critical global strategic consideration for organizations that aim to design and implement green EP systems or any innovation in procurement. Thus, this paper's findings are useful for academics and practitioners of big data and procurement in the region, specifically regarding how well they are prepared for greater reforms and structural changes that lie ahead.

2. Literature review and hypotheses

This paper aims to examine how EP can improve firms' ENP against the background of big data. In order to hypothesize and build a convincing conceptual model, we utilize some of the extensions of resource-based view (RBV) theory (Barney, 1991); natural resource-based view (NRBV) (Hart, 1995), and resource orchestration theory (ROT) (Helfat *et al.*, 2009; Sirmon *et al.*, 2011) This section introduces the reader to the concepts under investigation leading to the development of hypotheses and conceptual framework.

2.1. Theoretical background

The RBV theory focuses on firm-level determinants of company performance relative to traditional industry-level variables, which is widely regarded as a key advantage of RBV (Peng, 2001). The RBV holds that competitive advantage can be achieved more effectively by exploiting internal, rather than external factors, in contrast with the industrial organization view (Barney and Hesterly, 2010). Thus, RBV theory suggests that firms can be conceptualized as bundles of heterogeneously distributed resources across firms, and the resource differences persist over time (Barney, 1991). Moreover, firms with resources that satisfy the VRIN (valuable, rare, imperfectly imitable, non-substitutable) criteria can attain sustainable competitive advantage (Barney, 1991). However, the RBV's growing influence has provoked significant debate and critique in the academic community for years (Hitt *et al.*, 2016; Wu, L.-Y., 2010). RBV has been questioned for its failure to account for the biophysical environment, including the critical natural resource constraints that provide the context for a firm's creative ability and green capability building (Hart, 1995; Hart and Dowell, 2011). Hart (1995) proposed a natural resource-based view of the firm based on its relationship with the natural environment. Some researchers have suggested that the modern conceptualization has failed to recognize that natural processes, such as food protection, ecological services, and biological and cultural diversity, are in fact essential for the sustenance of human society and social organization (Hart and Dowell, 2011). Thus, the NRBV comprises three interrelated strategies: pollution prevention, product stewardship, and sustainable development in the RBV paradigm (Hart, 1995). Thus, the NRBV theory advances propositions for each of these strategies and points out their connections to achieve sustained competitive advantage and firm performance (Hart and Dowell, 2011). This may be done by initiating green practices to lead to a superior competitive advantage in terms of lower costs, reputation, legitimacy, future position, and long-term growth (Masoumik *et al.*, 2014).

Another shortcoming of RBV is that it explains competitive heterogeneity based on the premise that close competitors differ in their resources and capabilities in important and durable ways, affecting competitive advantage and disadvantage. Under this premise, RBV implies its static approach to competitive capabilities (Helfat and Peteraf, 2003). Therefore, a firm's performance depends on how managers properly use the available resources and the conditions surrounding that resource in the firm and market (Bromiley and Rau, 2016). Furthermore, Sirmon *et al.* (2011) argue that possessing VRIN resources does not guarantee the development of competitive advantages or the creation of value, and in order for organizations to realize value creation, they must accumulate, combine, and exploit resources. Hence, resource orchestration theory (ROT) has emerged to bridge this gap and provided the mobilizing vision to use firm resources by directing their use (Wales *et al.*, 2013). Consequently, ROT considers how a firm's resources are managed as equally important as what resources a firm has in its resource portfolio. Resource management, according to ROT, is the comprehensive process of structuring the firm's resource portfolio, bundling the resources to build capabilities, and leveraging those capabilities to create and maintain value and capabilities, and leveraging these capabilities to eventually realize a competitive advantage (Hitt *et al.*, 2011; Sirmon *et al.*, 2011). Structuring the resource portfolio includes utilizing processes such as acquiring, accumulating, and divesting to obtain the firm's resources for bundling and leveraging purposes. Bundling involves the processes (i.e., stabilizing, enriching, and pioneering) used to integrate resources to form capabilities; leveraging involves the set of processes such as mobilizing, coordinating, and deploying used to exploit capabilities to take advantage of specific markets' opportunities (Sirmon *et al.*, 2011).

In the area of big data, it was suggested that business analytics for organizational value creation depends on the roles played by the organizational decision-making processes, including resource orchestration processes, which requires examination and more profound understanding to further improve BDA capabilities (Singh and Del Giudice, 2019). This has led to more calls to utilize ROT in big data research (Rojo Gallego Burin *et al.*, 2020; Zeng and Khan, 2019; Zhang *et al.*, 2019; Zhu, Z. *et al.*, 2020). In their study on air pollution management, Zhang *et al.* (2019) propose a process model to illustrate developing BDA for sustainability. Zhang and Khan (2019) explicitly incorporate ROT into the domain of big data and identify entrepreneurial orientation as one of the key factors through which companies bundle and orchestrate the knowledge assets arising from big data for value creation (Dubey *et al.*, 2018). Although ROT is rarely used in BDA research, it is particularly beneficial for understanding the deployment of resources and capabilities such as EP and BDA. Unlike RBV and other extensions such as dynamic capability framework, in ROT, what matters the most is not BDA competency, but the fit or alignment of other resources and capabilities that create greater BDAC. In fact, Zeng and Khan (2019) suggested resources themselves may not create value for companies; they need to have internal practices and methods suited to putting resources into innovative value creation strategies

2.1. Environmental performance and rule of procurement

The concept of ENP is broad, and there is no common measure for judging how green an organization is. It has many indicators, including controlling harmful waste, such as carbon monoxide emissions, wastewater, and solid waste. Over the past three decades, many measures have been developed and continuously improved to achieve and measure organizations' ENP. One of the early efforts made to understand ENP within organizations was the study by Noci (1997), who concluded that green competence, environmental efficiency, green image, and life cycle cost are valuable capabilities to establish ENP and compliance measurement. Jaikumar *et al.* (2013) proposed evaluating organizations' ENP using the following components: (a) a separate environmental policy and concrete environmental action plans in the areas of energy-saving, air pollution control, effluent treatment before discharge, and solid waste management, (b) ongoing environmental education programs for employees, (c) priority given to environmental impact in the selection of new technology, (d) life cycle analysis conducted on products, (e) disclosure of environmental information related to its products and services, (f) availability of emissions and material usage data, (g) practice of environmental accounting, green supply chain management (SCM), and GP policy, and (h) involvement of the company in local community activities (Jaikumar *et al.*, 2013).

ROT was utilized recently in investigating environmental issues under new technology, as ROT emphasizes actions that effectively structure, bundle, and leverage firm resources such as knowledge, skills, routines, finance, information, and technologies. Wong *et al.* (2018) argue that there is a need for integrated management systems that drive top management, internal functions, suppliers, and customers to orchestrate the required resources to achieve aligned and balanced environmental, cost, and financial goals to achieve sustainable development. Resource orchestration capability allows firms to create formal and informal processes to facilitate knowledge transfer and encourage organizational learning to increase green innovation and improve EP (Wang *et al.*, 2020). Jiang *et al.* (2019) suggested using resource orchestration to align internal resources to improve global sourcing activities to maximize sustainable environmental performance. They also recommended investigating specific drivers and enablers in the supply chain that could lead to more sustainability. One of the key enablers is using the procurement function (Freeman and Chen, 2015; Jaikumar *et al.*, 2013; Shi, P. *et al.*, 2015). The role that procurement plays in ENP figures prominently in recent research. For example, Large and Thomsen (2011) conclude that the practice of green purchasing by green supplier assessment and green collaboration would improve not only a firm's procurement performance but also its ENP. Furthermore, Chan *et al.* (2012) look at procurement practices through the lens of green SCM and determine that GP practices will improve corporate performance and lead to improved ENP.

2.2. E-procurement

Ramkumar and Jenamani (2015) consider procurement as sustainable when it integrates requirements, specifications, and criteria that are compatible and in favor of protecting the environment, advancing social progress, and supporting economic development—specifically, by seeking resource efficiency, improving the quality of products and services, and, ultimately, optimizing costs. Thus, EP platforms come into play through their ability to innovate and offer proposals that are decisive for the conservation of natural spaces while limiting the consumption of energy or other resources and helping in the battle against global warming (Allal-Chérif, 2010; Raghavendran *et al.*, 2012). EP is defined as using Internet-based (integrated) ICTs to carry out individual or all stages of the procurement process, including searching, sourcing, negotiating, ordering, receiving, and post-purchase reviewing (Panayiotou *et al.*, 2004). An EP system, therefore, constitutes a platform that is specific to a network of purchasers and suppliers, enabling them to communicate and collaborate. The business benefits of EP systems—such as controlled spending; reduced requisition-to-order costs, cycle time, and maverick spending; and improved transparency and efficiency—are well established in the literature (Ramkumar and Jenamani, 2015).

Indeed, the concept of resource orchestration has been incorporated into the recent literature on e-commerce and e-business to understand the relationships among components of ICT processes and innovation to create business value and higher performance (Cui and Pan, 2015; Cui *et al.*, 2017; Miao *et al.*, 2018; Rojo Gallego Burin *et al.*, 2020; Zhu, J. *et al.*, 2018). It was revealed that, by utilizing this concept, firms could acquire technical and relational resources portfolios to design e-business processes to manage digital business activities along with supply chain actors; hence this shall motivate partners to be actively engaged in the e-business processes allowing firms to bring external resources into its operation. Besides, leveraging e-business operations capabilities enables a firm to manage digital business activities and supply chain actors. Hence mobilizing e-business operations capabilities at different processes levels can form requisite capability configurations to support the modern supply chain operations.

2.3. The relationship between e-procurement and environmental performance

The literature review has demonstrated that EP systems have rarely been investigated in the context of GP and ENP. Nevertheless, because EP calls for the use of electronic media and avoids the extensive use of paper and printing, it falls into the category of GP (Raghavendran *et al.*, 2012). Walker and Brammer (2012) investigated how sustainable procurement is affected by the extent of communication with suppliers and by the degree to which ICTs are implemented in the supply chain and concluded that EP provided the buyers with the ability to implement sustainable procurement policies in their supply relationships and achieve higher ENP. Moreover, Ramkumar and Jenamani (2015) identified 26 driving factors that can help in managing sustainable purchasing programs through the use of ICT and separated them into six categories: (a) centralized procurement governance, (b) automated process, (c) integration, (d) enabled supplier relationship, (e) spend data analysis, and (f) risk management.

The NRBV argues that it is a firm's bundle of resources rather than a product deployment of those resources that determines its competitive position (Hart, 1995). From the ROT perspective, specific sources can be synchronized to create a sustained competitive advantage. Since EP is using ICTs based systems to carry out procurement processes, an EP system can be viewed as an ICT-enabled resource for a firm and can serve as a source of competitive advantage (Barney, 1991). Nevo and Wade (2010) viewed ICT-enabled resources as having a more significant strategic potential than other organization resources in isolation. Furthermore, ROT emphasizes the importance of acquiring and organizing resource portfolios of combined platform architecture to develop e-business operations capabilities (Zhu, Z. *et al.*, 2020). This ability to bundle and leverage ICT-enabled resources across internal functions, suppliers, customers, and other stakeholders through integration is arguably an effective means to enable resource orchestration to achieve organizational goals such as environmental sustainability. Teo *et al.* (2017) suggest that firms can use ICT-enabled resources to develop the capabilities required using green technologies, integrate them with interfirm technologies, and develop and deploy processes to harness them. In other words, firms can use ICT-enabled resources to develop unique capabilities (Teo *et al.*, 2017). Thus, ICT-enabled resources such as EP can be infused into a firm's business objectives (for example, sustainability initiatives) through *complementarity* and *co-specialization* (Tippins and Sohi, 2003, p. 747). As such, a firm's EP is enhanced by appropriate ICT resources and practices. Consequently, we can conclude that, based on ROT and NRVB, it is logical to suggest that a relationship exists between the organizations' EP and organizations' ENP. Hence, this reasoning leads to the following hypothesis:

H1. E-procurement has a relationship with organizations' environmental performance.

2.4. Big data analytics capabilities

Big data is an umbrella term referring to massive or complex datasets for which working with conventional data processing applications is insufficient (Wu *et al.*, 2016a). Thus, it is widely recognized as one of the most powerful drivers for promoting productivity, improving efficiency, and supporting innovation when utilized effectively. Big data has also been defined primarily using the "five Vs": volume, variety, velocity, veracity, and value (Gandomi and Haider, 2015, p. 139). Labrinidis and Jagadish (2012) further break down extracting insights from big data into five stages that form two main subprocesses: data management and analytics. Data management includes the processes and supporting technologies to acquire and store data and prepare and retrieve it for analysis. Analytics, on the other hand, refers to the techniques used to analyze and acquire intelligence from big data. Thus, big data analytics (BDA) can be viewed as a subprocess in the overall insight extraction process from big data (Labrinidis and Jagadish, 2012).

Over the past decade, big data has significantly impacted hospitality, transportation, health, governance, and e-commerce (Akter and Wamba, 2016; Victor and Maria, 2018) and is increasingly seen as having the potential to deliver a competitive advantage throughout the supply chain (Sanders, 2014). Big data applications can be linked to SCM across fields such as procurement, transportation, warehouse operations, marketing, and smart logistics (Anitha and Patil, 2018). With proper decision making and experience, big data can provide a noticeable contribution in respect of raw material prices, lead time, environmental and business risks suppliers might face in a particular geography, thus achieving visible improvement in procurement (Chopra, 2019). BDA could help procurement operations make decisions in three critical areas. The first area is risk management. DBA provides procurement functions with greater access to historical and real-time data (Moretto et al., 2017); hence, they will be capable of detecting problems, monitoring supplier behavior, and measuring customer satisfaction levels, cash flow, lead times, and cost (Hickey, 2018). The second key area is supplier compliance. Nowadays, suppliers are evaluated based on a broad spectrum of parameters, consistent with their strategic importance (Moretto *et al.*, 2017). BDA gives procurement functions the ability to compare each transaction with the supplier contract linked to, measuring its performance and compliance (Hickey, 2018; Moretto *et al.*, 2017). The third key area is predictive analysis. Procurement processes would benefit from adopting a large amount of structured data with reporting and predictive purposes and becoming predictive rather than reactive (Moretto *et al.*, 2017). Therefore, by configuring specific business rules, ICT-based procurement systems would be able to predict demand for a certain requirement within an organization and then ensure that the correct resources are sourced based on quality, price, and supply (Hickey, 2018).

2.5. The relationship between EP and BDAC

According to the RBV, resources can be both tangible and intangible, the former including the capital, buildings, IT infrastructure, network, connectivity, and a data source; the latter including employee experience, knowledge, business acumen, problem-solving abilities, leadership qualities, and relationships with others (Barney, 1991). Zeng and Khan (2019) suggested that the process of resource management is referred to as managerial capabilities by bridging two related frameworks: resource management and asset orchestration under ROT. Sirmon *et al.* (2007) highlighted the importance of bundling capabilities related to technological development and harnessing so that the industry boundaries and competitors could become clearer. In the following two subsections, we aim to bundle similar big data capabilities that can be orchestrated from the previous literature.

2.5.1. Technological capabilities

When it comes to technology, big data adaption requires the existence of a tangible technological infrastructure (TI) such as cloud computing, big data systems, No-SQL database, cognitive systems, deep learning, and other artificial intelligence techniques to integrate conventional ICT systems into a unified analytics system (Shi, Z. and Wang, 2018). Furthermore, data infrastructure interoperability with other systems and applications must also be ensured before launching any big data project (Lnenicka and Komarkova, 2019). Given the vast technological resources required to operate in a big data environment, many have followed ROT to bundle such resources to study and utilize them effectively. For example, classify big data tangible technological resources into three categories: (a) data connectivity, which refers to a technological resource that enables the effective sharing of information among different systems and applications; (b) technology, which they considered as novel technologies that are capable of handling volume, variety, veracity and velocity to extract valuable and authentic information; and (c) basic resources, such as investing in big data and its related technology and tasks, to allow organizations to explore the standard operating procedures to implement big data initiatives. Meanwhile, Mikalef *et al.* (2019b) argue that tangible technological resources could not by themselves create BDAC and require other technological intangible resources, such as the data availability (DA). Data, such as texts, weblogs, GPS location information, sensor data, graphs, videos, audio, and more online data, are becoming more sophisticated and diverse. Therefore, data requires different tools and technologies to handle and store (Forsyth, 2012). In fact, the availability of data from various sources (internally and externally) has enabled the large-scale adoption of data-driven decision-making capability (Karduck and Chitlur, 2016). Consequently, the value of BDA was the result of the maturity of tangible (ICT infrastructure) and intangible resources (data; (Gupta and George, 2016; Jeble *et al.*, 2018; Xu and Kim, 2014). Hence, this paper is suggesting that the technological capabilities (TC) bundle includes technological infrastructure and availability of data.

2.5.2. Human capabilities

Human resources were also found to be another crucial capability in the big data environment. Human learning is considered an important capability to achieve higher performance and should be regarded as a "high order capability" (Prieto and Revilla, 2006). Learning involves both individual and organizational mechanisms to experiment with new procedures and improve existing routines through collaboration and partnerships (Teece, 2007). Therefore, human skills are of enormous relevance to learning; their value depends upon their employment, in particular, in organizational settings (Eisenhardt and Martin, 2000). In fact, in the beginning, ROT was considered from the resource management framework, which focused on the importance of managerial skills in structuring, bundling, and leveraging a firm's resources for superior performance and competitive advantage. (Sirmon *et al.*, 2007). Thus, managerial actions can mediate the resource–performance linkage, thereby providing support for the manager's role in creating a competitive advantage (Badrinarayanan *et al.*, 2019; Sirmon *et al.*, 2011). However, recent studies have suggested that human capabilities (HC) required to work in a big data environment were to be based on two constructs/bundles pertaining to the respective type of skills: technical and managerial skills (Jeble *et al.*, 2018; Mikalef *et al.*, 2019b; Wamba *et al.*, 2017). In a similar vein, this paper proposes employee skills and managerial experience in the big data environment as two essential aspects of a firm's HC as shown in Table 1.

Nowadays, many organizations are making use of procurement to enhance their managerial decisions, which will help in eliminating possible risks and maximizing profit (SpendEdge, 2017). When a data-driven EP system is launched and implemented, procurement in various organizations will become easier to implement, leading to cost reduction and increasing profits. Further, because EP systems are embedded and/or supported by ICT systems, the modularity at the system level certainly helps modularity in the business processes (Xu and Kim, 2014). Thus, EP systems, data, and applications can merge with big data technological capabilities (TC) to improve the system's modularity and support new analytical demands. Human capabilities (HC) were also found to be a crucial element in e-business transformation to develop and critically evaluate business cases, incorporating substantial alterations to the business model with uncertain information and coordinating with all stakeholders. ROT, ICT capabilities such as EP can provide organizations with additional information that helps generate novel insights concerning ways to better bundle their resources toward the pursuit of new entry opportunities such as big data and help managers improve their decision-making processes and perspectives (Wales *et al.*, 2013). Therefore, it follows that if an organization has a mature EP system, it can enhance BDAC (tangible and intangible), to generate better decision-making and greater organizational performance. Hence, this reasoning leads to the following hypothesis:

H2. E-procurement has a positive influence on big data analytics capabilities.

Table 1
Big Data analytics used in the paper

BDAC	Resources	Description	Highlighted by
Technological capabilities	Technology infrastructure	Novel technologies that are capable of handling the challenges posed by gigantic, diverse, and fastmoving data such as cloud computing, big data systems, No-SQL database, cognitive systems, deep learning, and other artificial intelligence techniques	(Arifiani *et al.*, 2019), (Gupta and George, 2016), (Wamba *et al.*, 2017), (Jeble *et al.*, 2018) (Akter *et al.*, 2016),
	Data	Availability and accessibility of enterprise-specific data, which are created as a result of the firm's internal operations such as inventory updates, accounting transactions, sales, and human resource management	(Gupta and George, 2016), (Wamba *et al.*, 2017), (Jeble *et al.*, 2018), (Akter *et al.*, 2016)
Human capabilities	Managerial Experience	Firm-specific skills developed by managers over time that allows them to understand the current and predict the future needs of the organizations and to have a sharp understanding of how and where to apply the insights extracted from big data	(Gupta and George, 2016), (Wamba *et al.*, 2017), (Jeble *et al.*, 2018), (Ferraris *et al.*, 2019),
	Employees skills	The know-how required by employees to use new forms of technology to extract intelligence from big data	(Gupta and George, 2016), (Wamba *et al.*, 2017), (Jeble *et al.*, 2018), (Ferraris *et al.*, 2019)

2.6. The mediating role of big data capabilities

The role of big data in preserving the environment has been debated in recent literature. On one hand, some suggest that big data may consume huge computing power and resources that may increase of energy consumption and other resources (Estevez and Wu, 2015); resulting in creating what is called a big data's "green challenge" (Atat *et al.*, 2018, p. 73605). On the other hand, is considered a technological innovation that could utilize big data technology to help preserve the environment (Wu *et al.*, 2016b). Further, our literature review suggests that adopting traditional IT-driven procurement platforms is not a best practice for building GP into the supply chain. Hence, to increase the overall ENP of the supply chain through EP, further improvement to existing EP platforms is required (Adjei-Bamfo *et al.*, 2019; Raghavendran *et al.*, 2012; Wahid, 2012). Interestingly, Talamo and Atta (2019) investigate the influence of the sustainable procurement international standard ISO 20400:2017 on sustainable facility management practices against the background of Internet of Things (IoT) and BDA, revealing that big data analytics capabilities (BDAC) may represent a significant driver for improving the monitoring and control processes of sustainable service performance.

Hence, with BDAC, organizations can possess vast and rich sources of social, human behavioral, and environmental data. Therefore, conducting a green spending analysis was found to speed up and unblock process changes within an organization (Barraclough *et al.*, 2012; Gandomi and Haider, 2015; Gijzen, 2013), which can employ big data in two forms: first, as evidence that they comply with government regulations on their industry and sector, and second, to launch investigations to determine the cause of an environmental problem (Mason, 2018). Moreover, collecting big data can be useful in modeling and testing an array of different scenarios for sustainably transforming the production and consumption of energy, improving food and water security, and eradicating poverty. Therefore, where conventional EP platforms fail, organizations can implement many ENP enablers and enhance their monitoring and control processes for ENP using the emerging BDAC (Dubey *et al.*, 2017; Talamo and Atta, 2019). Hence, this reasoning leads to the following hypothesis:

H3. BDAC mediates the relationship between e-procurement and environmental performance.

2.7. Conceptual model

The model (Figure 1) conceptualized from the paper's theoretical exploration can be explained by ROT and NRBV. The ROT emphasizes actions that effectively structure, bundle, and leverage a firm's resources, including the firm's internal resources. On the other hand, the NRBV argues that access to rare resources leads to competitive performance. Resource orchestration helps create a shared vision to achieve better environmental performance across supply chains (Hart, 1995; Sirmon *et al.*, 2011). Therefore, BDAC was repeatedly identified as a multidimensional, hierarchical construct with various subdimensions determining the primary dimensions. As such, we propose BDAC as a third-order construct with two second-order dimensions (TC and HC), and we contribute to extending this stream of research in the big data in

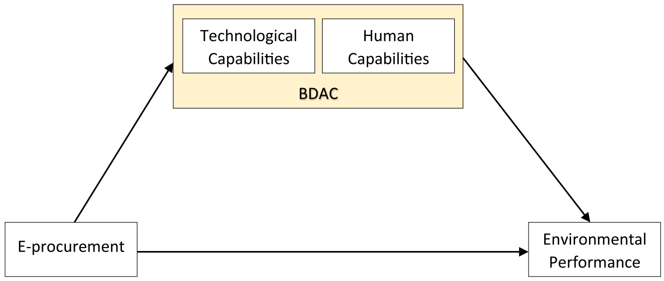

Figure 1. Conceptual model

the procurement context.

3. Methods

3.1. Survey design and study setting

This quantitative study used a web-based survey to collect data from procurement professionals in the UAE. Reason for selecting the UAE because the UAE has endeavored to enhance its economy's sustainability and promote a green economy in the last six years. In 2015, the UAE joined two major international networks composed of policy experts hosted by the United Nations Environment Program (UNEP) to gain vital knowledge regarding the best global practices in green public procurement and eco-labeling programs (Albawaba, 2015). In 2018, the UAE launched its green business toolkit to offer entry-level guidelines on establishing a business as a green entrepreneur in three key areas: green office, green procurement, and green product. This toolkit identifies essential items in green procurement: energy efficiency, low emissions, non-use of hazardous materials, and recyclability, extending to social aspects such as ethical conduct and community development (UAE Ministry of Climate Change & Environment, 2018).

3.2. Survey Instrument

A survey pre-testing was realized with two experts working on BDA-related projects. All the constructs used in the paper were derived from prior studies and adapted to fit our research context of BDA in the supply chain context. The first expert, an academic whose research expertise is in BDA in the supply chain, was asked to evaluate the questionnaire's content validity. The second expert was a professional, a senior procurement manager, who assessed the questionnaire's face validity. The survey instruments were slightly modified based on feedback from the experts. The items were measured using a five-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree." Appendix A provides all scales and items.

3.3. Sample size and data collection

A suitable sample group for the target population for this paper, namely, the procurement functions in UAE firms, was required for data collection. This paper is mainly interested in targeting firms that have already adopted business intelligence practices in their procurement function. Using word of mouth, we have located 23 public and private organizations in the UAE already using different AI-based procurement platforms. Then, we have sent email invitations to these organizations with the statement of the purpose of the paper. Only eleven organizations have responded to this email and directed us to the point of contact (POC) in their entities. After contacting each of these POCs, we learned that the total number of employees working in procurement within these organizations is around 340, which shall be the target for this paper. In June 2020, after permission was obtained from each organization, a survey was sent via a survey administration software platform (SurveyMonkey) to 340 procurement professionals working in public and private organizations located in Abu Dhabi. A total of 241 respondents completed the survey, producing a response rate of 70%. To ensure that irrelevant results would not be recorded, a question that checked whether respondents were working in a procurement function in their organization was used to eliminate 25 responses, leaving a final sample of 216. Finally, 76% of the sample represents the public sector, where 24% are from the private sector.

To overcome the issue related to bias in the survey-based approach, we first tested for non-response bias using analysis of the variance techniques suggested by Armstrong and Overton (1977). We compared the responses of early respondents (first 25%), late respondents (last 25%), and a sample of non-respondents which did not indicate any response bias across the variables. Then, we addressed the issue of Common Method Bias (CMB) by using full collinearity assessment as recommend by Kock (2015). Using SmartPLS, we found all factor-level full collinearity VIF values below the proposed value of 3.3 (Kock, 2015). This indicates that the CMB was not an issue in the dataset.

3.4. Statistical analysis

Data analysis was realized using a partial least squares structural equation modeling (PLS-SEM) tool called SmartPLS 3.0 to simultaneously assess the measurement instrument and conceptual model. This approach was considered appropriate because PLS can deliver valid results even for small sample sizes (Chin, 1998). SmartPLS 3.0 also allows the testing of higher-order models. In this paper, BDAC is conceptualized as a third-order construct with two second-order dimensions that TC and HC can explain. Modeling BDAC as a higher-order model is beneficial as it reduces the number of relationships between BDAC and EP (Figure 2). Also, higher-order constructs provide a means for lowering collinearity among formative indicators by offering a vehicle to re-arrange the indicators and/or constructs across different concrete subdimensions of the more abstract construct (Hair Jr *et al.*, 2016). In general, the higher-order model approach allows the path model to be more parsimonious and easier to understand.

According to Sarstedt *et al.* (2019), there are four higher-order constructs: reflective-reflective, reflective-formative, formative-reflective, and formative-formative. Prior studies on higher-order constructs in PLS-SEM have shown that reflective-reflective and reflective-formative higher-order types feature prominently in different fields (Sarstedt *et al.*, 2019). In this paper, a reflective-formative higher-order construct is being conceptualized in this research based on the literature review. Also, there are two commonly used methods used in the literature to validate and assess a higher-order construct; the repeated indicators approach and the two-stage approach (Hair Jr *et al.*, 2016). In this paper, the path model was established and estimated using a two-stage approach (Becker *et al.*, 2012; Ringle *et al.*, 2012), which is thought to overcomes many of the problems when using reflective-formative higher-order models and more suitable for a small sample size (Sarstedt *et al.*, 2019). The first stage of the two-stage approach starts with applying the standard repeated indicators approach and testing it to assess the outer loadings only without checking the model's consistency or reliability. Then, in stage two, the construct scores are used as indicators in the higher-order construct's measurement model.

Since we conceptualized a third-order path model for the paper, the analysis was conducted the two-stage approach in three phases. In the first phase, we applied the repeated indicated in the path model. Then we conducted a measurement model assessment for the 1st order components based on the standard model (Figure 3) described in the two-stage approach, which draws direct relationships between all the measurement items and constructs. In phase two, as suggested in the two-stage approach, the latent variables (LVs) for (ME, ES, TC, and DA) that were captured in phase one were saved in the original data file, and the analysis was conducted again as shown in Figure 4. In the third phase, all the LVs for (TC and HC) captured in phase two were again saved in an amended data file. This analysis was conducted to create and

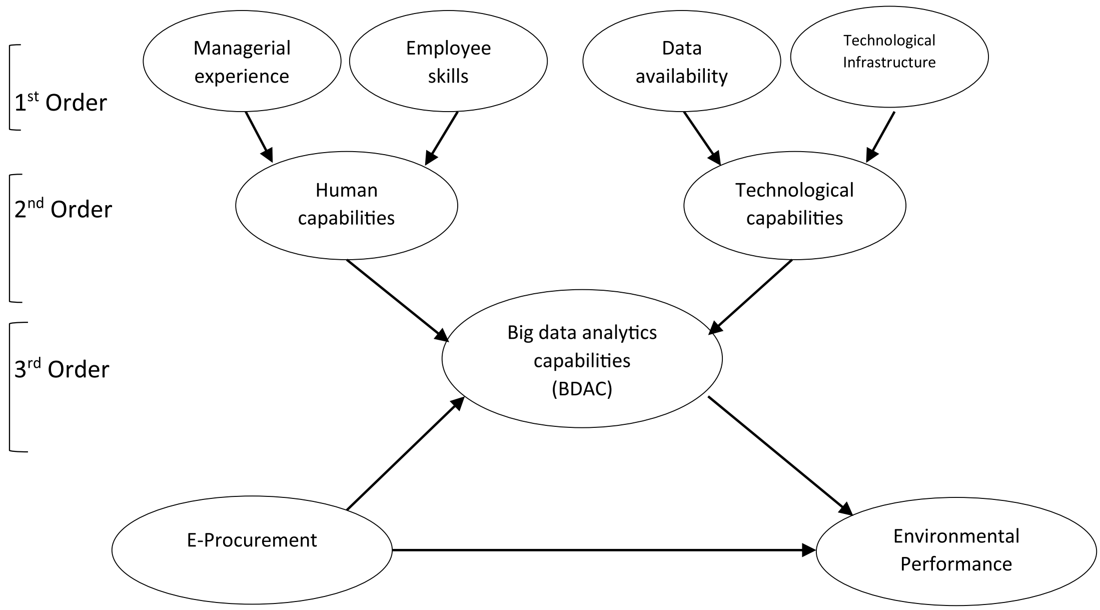

Figure 2. Statistical model

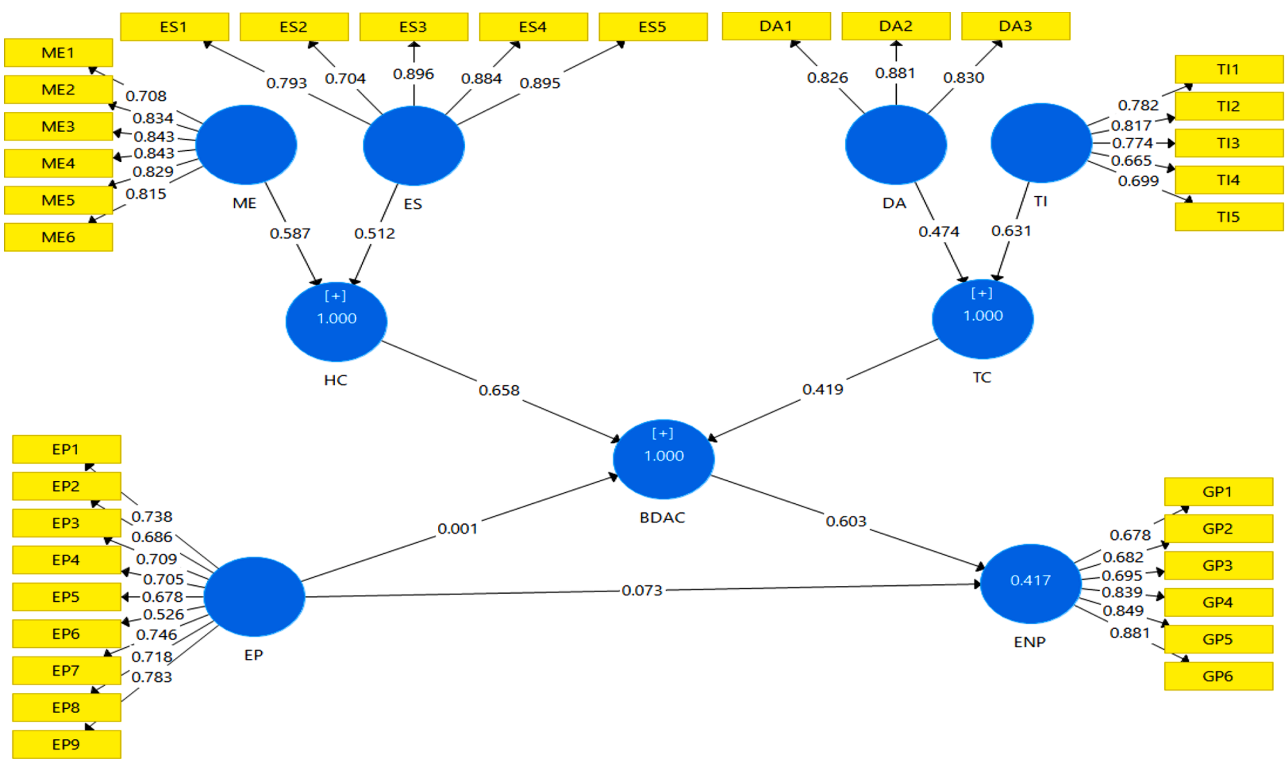

Figure 3. Phase one path model

estimate the model and test the hypothesis, as shown in Figure 5.

Before assessing the measurement model, we considered endogeneity by reviewing relevant literature that focuses on explanation. Our review of the literature on employing PLS-SEM methods in SmartPLS showed no explicit reference to endogeneity. It was suggested to address the PLS-SEM endogeneity issue in the research design stage by focusing on theory to develop constructs and multiple constructs (Antonakis and House, 2014; Sarstedt *et al.*, 2020). Hence, we followed Mikalef *et al.* (2019b) and multiple constructs theoretical development approach and developed our constructs consisting of multiple items and sub-constructs (e.g., BDAC).

PLS model assessment and interpretation comprises two stages: (1) assessing the reliability and validity of the measurement model; and (2) evaluating the structural model. To evaluate the measurement model's reliability and validity, we compared the values for Cronbach's α, composite reliability (CR), and average variance extracted (AVE). With respect to convergent validity, we checked the factor loadings for all measures to check for abnormalities in stage one. In stage three, we tested the measures' discriminant validity by examining whether the AVE's square root for each construct was larger than its correlation with other factors (Kline, 2015). Furthermore, multiple criteria were also used to evaluate the goodness of model fit, including the standardized

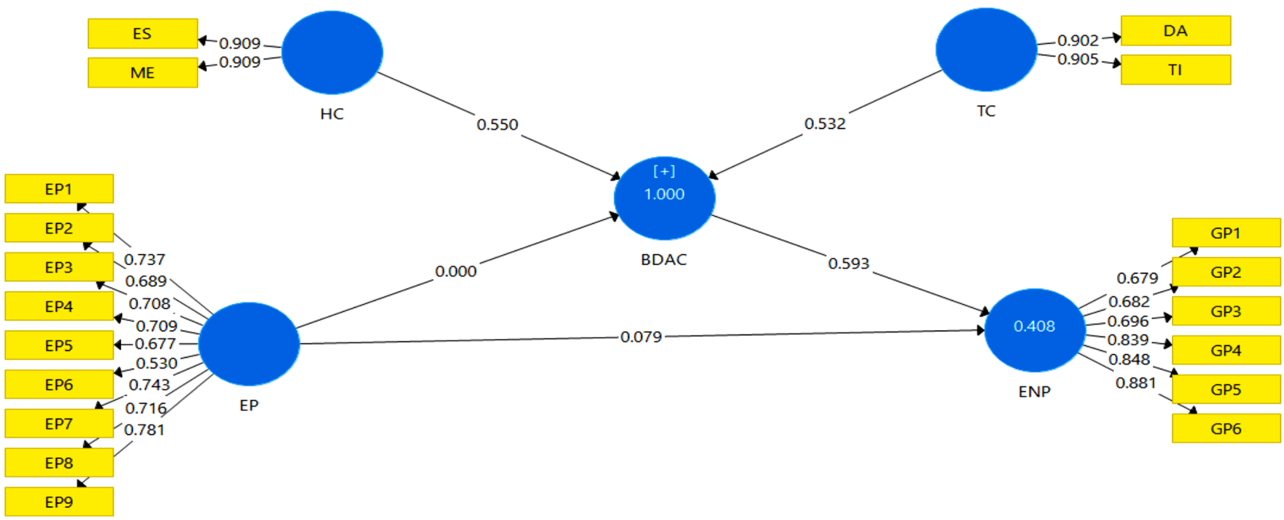

Figure 4. Phase two path model

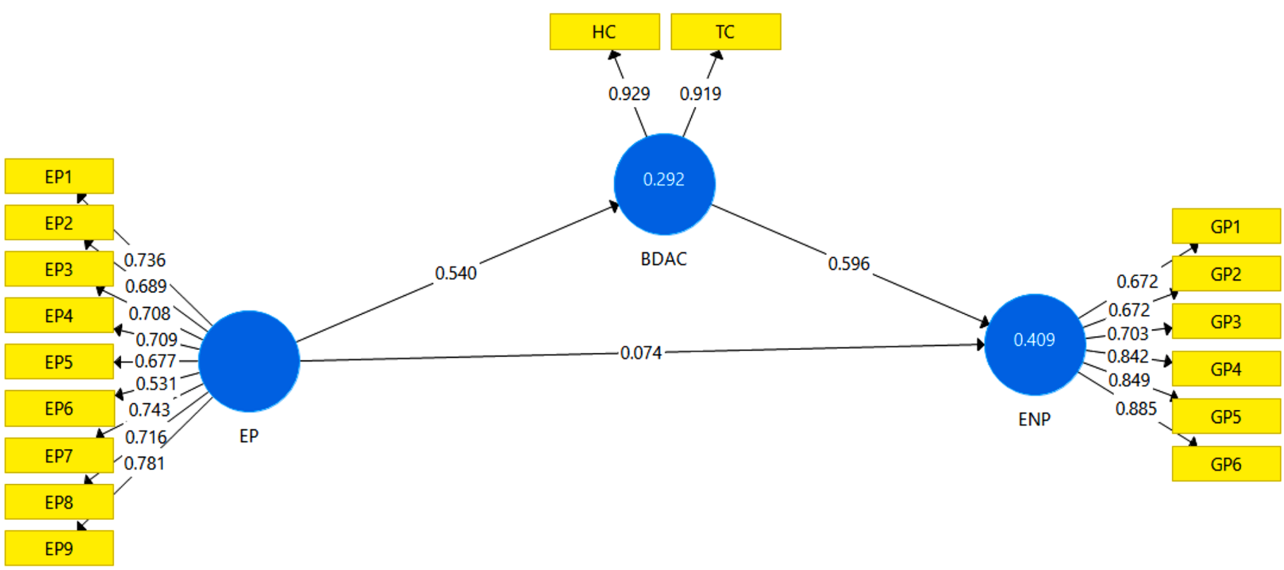

Figure 5. Phase three path model

root mean square residual (SRMR) and normed fit index (NFI) in phase three. These tests were conducted to measure the predictive performance of the measurement model. Once the measurement model was determined to be adequate, we evaluated the structural model and tested the hypotheses.

4. Results

4.1. Assessing the measurement model

We assessed the reliability constructs using the internal consistency measure in each analysis phase. After running the first phase (the standard path model) on SmartPLS 3.0, we received an unacceptable AVE value of .493 for EP. Therefore, EP6 was dropped to improve the model's internal consistency and reliability and avoid having an issue in phase three. Next, we ran all the three phases resulting of the data presented in Table 2 (which shows the results of validity and reliability tests), demonstrating that all values for Cronbach's α and CR were above .70; the values for the AVEs ranged from .526 to .854 indicating acceptable reliability in all phases.

Table 2
Results of confirmatory factor analysis

	Measures	Items	Cronbach's Alpha	CR	AVE
Phase One	Managerial Expertise	6	.897	.921	.662
	(ME)	5	.892	.921	.702
	Employees Skills (ES)	3	.801	.883	.716
	Data Availability (DA)	5	.802	.864	.562
	Technological Infrastructure (TI)				
Phase Two	Human Capabilities (HC)	2*	.791	.905	.827
	Technological	2**	.775	.899	.816
	Capabilities (TC)				
Phase Three	Big Data Analytics	2***	.827	.921	.854
	Capabilities (BDAC)	8	.870	.898	.526
	E-procurement (EP)	6	.865	.899	.602
	Environmental Performance (ENP)				

* Two items captured from phase one (ME and ES), ** Two items captured from phase one (DA and TI), *** Two items captured from phase two (HF and TC)

After the model was improved, confirmatory factor analysis was used to test our research model's measures. Table 3 shows the weights and loadings for the test. All measures displayed moderate loadings, indicating acceptable convergent validity.

After completing all phases, we checked the discriminant validity of the measures by determining whether the square root of the AVE for each construct was larger than its correlation with the other factors. As shown in Table 4, all construct correlations were less than .924. The AVE's square root for each construct was larger than the correlation between any pair of factors, confirming the scale's discriminant validity. Also, all items had strong factor loadings on their constructs. Overall, the measurement model displayed adequate discriminant validity.

Finally, before testing the structural model, we checked its fitness. The goodness of fit results obtained from SmartPLS 3.0 included an NFI value of .747, below the recommended value of .95. However, the SRMR value was .080, which is considered acceptable by Hu and Bentler (1999). Hence, the model can be considered to have a good fit.

4.2. Evaluating the structural model

Adopting an acceptable measurement model, we proceeded to test the proposed hypotheses using SmartPLS 3.0. Bootstrapping analysis was conducted in 5000 replications for phase three path model. The results of this analysis are depicted in Table 5, which shows that H1 was not supported ($\beta = .080$; $t = 1.169$; $P = .239$), demonstrating that EP has no relationship with ENP. However, H2 was supported ($\beta = .054$; $t = 9.772$; $P < .001$), demonstrating that EP has a positive influence on BDAC. Furthermore, the mediation test results revealed significant indirect effects between EP and ENP ($\beta = .040$; $t = 7.758$; $P < .001$), demonstrating the full mediation effects of BDAC on the relationship between EP and ENP.

Table 3
Factor loadings, weights, and t-values

Model Construct	Measures	Factor Loading	Weights	t-Value
Managerial Expertise (ME)	ME1	.708	.179	14.758
	ME2	.834	.210	27.886
	ME3	.843	.224	33.032
	ME4	.843	.206	35.115
	ME5	.829	.204	29.646
	ME6	.815	.205	29.811
Employees Skills (ES)	ES1	.793	.234	27.232
	ES2	.704	.190	14.366
	ES3	.896	.262	59.059
	ES4	.884	.240	44.854
	ES5	.895	.261	57.605
Data Availability (DA)	DA1	.826	.396	31.834
	DA2	.881	.391	39.598
	DA3	.830	.396	36.521
Technological Infrastructure (TI)	TI1	.782	.264	20.684
	TI2	.817	.277	24.675
	TI3	.774	.261	17.836
	TI4	.665	.270	15.890
	TI5	.699	.267	18.159
E-procurement (EP)	EP1	.738	.148	15.366
	EP2	.686	.150	13.924
	EP3	.709	.169	15.442
	EP4	.705	.169	16.859
	EP5	.678	.165	11.901
	EP6	.526	.115	8.039
	(dropped)	.746	.189	17.356
	EP7	.718	.152	15.167
	EP8	.783	.162	20.095
	EP9			
Environmental Performance (ENP)	GP1	.678	.165	10.434
	GP2	.782	.207	14.416
	GP3	.695	.165	10.983
	GP4	.839	.231	31.597
	GP5	.849	.246	28.413
	GP6	.881	.260	42.259

Table 4
Discriminant validity matrix

	BDAC	ENP	EP
BDAC	.924		
ENP	.636	.776	
EP	.530	.406	.725

Table 5
Hypothesis test results

Hypotheses	*P*-Value	*B*	*t*-value	Results
H1: EP → ENP	.239	.080	1.169	Not Supported
H2: EP → BDAC	.000	.054	9.772	Supported**
H3: EP → BDAC→ ENP	.000	.040	7.758	Supported**

Significant at $P^{**} < .01$

5. Discussion

This paper investigated the causal relationships among perceived ENP, EP, and BDAC amid procurement professionals in the UAE, while also performing causal mediation analysis to identify BDAC's mediating effect on the relationship between EP and ENP. To achieve this purpose, we utilized RBV, NRVB, and ROT theories to conceptualize a BDAC model as a multidimensional, hierarchical construct with various sub-dimensions determining the primary dimensions. Once orchestrated and appropriately bundled, they will be able to sense, seize and reconfigure procurement operations by rendering them more agile to transform traditional EP to Green EP.

5.1. Summary of findings

First, we tested the hypothesis of was whether EP has a relationship with ENP. The results show that the perceived implementation of EP did not have a significant effect (whether positive or negative) on ENP. This finding contrasts with previous suggestions (Raghavendran *et al.*, 2012; Ramkumar and Jenamani, 2015; Walker and Brammer, 2012), indicating a correlation between EP and ENP. Although this paper determined that EP is not contributing to ENP, nevertheless, if organizations want to improve ENP through procurement, they may still utilized EP to achieve other environmental initiatives, such as monitoring and reporting of environmental information related to procurement (Broomes, 2016; Kähkönen *et al.*, 2018; Townsend and Barrett, 2015), and inserting environmental criteria in procurement in areas such as energy-saving, air pollution control, and waste management (Dada *et al.*, 2010; Townsend and Barrett, 2015).

Second, we tested the hypothesis of whether EP has a positive impact on BDAC. The results show that EP positively affects BDAC, and hypothesis H2 is accepted. As such, our findings are consistent with our investigation of the literature and ROT and from previous studies that suggested that most of the procurement organizations excel at leveraging analytics (McGovern, 2014). However, our findings probably offer the first empirical evidence to validate EP's causal impact on BDAC. It suggests that more mature organizations in EP have the higher skills and capabilities required to work successfully under big data environment.

Finally, our third hypothesis predicted that BDAC mediates the relationship between EP and ENP. The findings supported this hypothesis, and when BDAC was introduced as a mediator between EP and ENP, a significant and positive effect was found on ENP, indicating full mediation. These findings suggest that organizations that aim to improve ENP should immediately adopt big data technologies and their analytical powers. By orchestrating BDAC capabilities, organizations shall be able to process and analyze huge environmental data and conduct faster green spending analysis to make greener decision-making in procurement, creating maximum value creation (Barraclough *et al.*, 2012; Dubey *et al.*, 2017).

5.2. Contributions and implications

This research offers some key theoretical contributions. First, we draw on the RBV, NRBV, and ROT to conceptualize a third-level order path model that integrates BDAC (human capabilities and technological capabilities) with ICT-based procurement capabilities and firms' environmental performance. Second, BDAC has been investigated extensively as an extension of RBV, which is a dynamic capability, by looking at how to leverage these resources and capabilities independently in a strategic manner (Dubey *et al.*, 2017; Jeble *et al.*, 2018; Wamba *et al.*, 2017). Thus, this paper contributes to big data literature by utilizing ROT to advance the theoretical understanding of BDAC in relation to supply chain, specifically ICT-based procurement, by viewing these resources as interrelated resources that require bundling them to maximize value creation. Further, by making a distinction between human and technological resources and understanding the value creation process based on environmental performance, it could provide a more robust explanation for resource orchestration networks for future studies on BDAC's role in preserving the environment. This paper also extends prior research on sustainable development based on NRBV and ROT by exploring key predictors of BDAC in greening EP. Specifically, our findings validate the fundamental roles of human capabilities and technological capabilities in green EP under big data environment. That is likely why Khan (2019) suggested that big data should be considered planning and implementing in the modern supply chain from a holistic perspective. Second, the paper validates the mediation influence of BDAC on the relationship between EP and ENP. BDAC has been recognized as an essential concept in sustainable development research (Shokouhyar *et al.*, 2020; Song *et al.*, 2019) and in ICT-based procurement literature (Barraclough *et al.*, 2012; Handfield *et al.*, 2019). To date, very few studies have integrated the concept while studying the relationship between EP and ENP in the context of BDA. Therefore, this paper fills this gap by extending analytics research in BDA and sustainable development literature.

There are also several practical implications of this paper due to BDA's operational and strategic potential globally. First, the proposed model can serve as a baseline model for EP assessment during the analysis and design of BDA applications for organizations that aim to achieve higher EP. Second, this paper identifies a set of capabilities (i.e., managerial experience, employees' skill, technological infrastructure, and data availability) and components that may lead to high-level organizational performance and EP effectiveness using BDA. Third, the paper proposes not only a combination of skills required for future leaders and managers but also the conditions under which that may lead to superior firm performance in big data environment. Fourth, this paper provides a list of attributes that may guide human resource and training departments during their career and recruitment planning decisions for future and existing big data projects implementation and thus foster better utilization of BDA tools.

6. Limitation and future research

Although this paper produced several encouraging results, it has some limitations that should be acknowledged. First, it has a relatively small sample size of 216, divided between the public and private sectors. Future work can access a larger sample drawn exclusively from either the public or private sector to be used as a comparison term. Second, this paper only examined limited numbers of BDAC. It may be profitable to pursue an investigation of other variables not included in this paper, such as those of data-driven culture, organizational learning, and procedural practice (Jeble *et al.*, 2018; Mikalef *et al.*, 2019b), or even looking at BDAC from different perspectives, such as big data management capability, big data technology capability, and big data talent capability (Akter *et al.*, 2016). The third limitation is that data from this paper were collected only in one country. Future research could expand this paper by collecting data from more countries with different cultural backgrounds considering cultural factors (e.g., language, developed vs. developing countries). Finally, this paper employed a cross-sectional research design for data collection. Hence, it would be useful to employ a case study or a longitudinal study to reduce any CMB and endogeneity-related concerns and capture its stability across time or settings.

7. Conclusion

Although BDAC for sustainable development has gained momentum in recent years, it requires large-scale practice and innovation in the procurement function to enhance environmental performance. On the BDAC's technology side, organizations must focus on assuring data infrastructure interoperability with other systems and applications and the availability of accessible data to be used for analysis. Similarly, the human side of BDAC shall focus on training management and employees on data technology, analysis, and developing technical and relational knowledge to develop skilled procurement analysts. Both public and private organizations can simultaneously get the most of big data and green procurement by leveraging their ICT infrastructure, data, and human capital to achieve environmental performance.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors

Appendix A

Construct measurement instruments

Construct	Derived From	Measures
E-Procurement (EP)	Brandon-Jones (2006)	EP1. The e-procurement system ensures orders are processed quickly EP2. The e-procurement system ensures orders get to suppliers quickly EP3. The e-procurement system reduces the lead time of orders EP4. The e-procurement system ensures that orders arrive on time EP5. The e-procurement system has the right number of suppliers loaded EP6. The e-procurement system has the right number of catalogues loaded EP7. The e-procurement system is always available EP8. The e-procurement system moves quickly from one screen to the next EP9. The e-procurement system allows easy navigation through the order process
Environmental Performance (ENP)	Large and Thomsen (2011)	GP1. We have achieved a reduction of pollution and waste. GP2. We have improved compliance with our organization environmental policy. GP3. We have increased the level of recycling.

(*continued on next page*)

(*continued*)

			GP4. We have preserved the environment. GP5. We have improved the environmental reputation of our organization. GP6. We have improved the overall environmental performance of our organization.
Human Capabilities (HC)	Jeble *et al.* (2018)	Managerial Expertise Employees' Skills	ME1. Our procurement managers understand sustainable business development needs of other functional managers, suppliers and customers ME2. Our procurement managers can coordinate big data and predictive analytics related activities in ways to support other functional managers, suppliers and customers ME3. Our procurement managers can work with functional managers, suppliers and customers to determine opportunities that big data might bring to our business ME4. Our procurement managers can anticipate the future business needs of the other functional managers, suppliers and customers using big data ME5. Our procurement managers have good sense of where to use big data ME6. Our procurement managers can understand and evaluate the output generated from big data. ES1. We provide big data related training to our procurement employees ES2. We hire new procurement employees that already have the big data and predictive analytics skill ES3. Our procurement staff has right skills on big data analysis to accomplish their jobs successfully ES4. procurement staff has suitable education on big data analysis to fulfill their jobs ES5. Our procurement staff is well trained on big data analysis
Technological Capabilities (TC)	Mikalef *et al.* (2019a)	Data Availability Technological Infrastructure	DA1. We have access to very large, unstructured, or fast-moving data for procurement analysis DA2. We integrate data from multiple sources into a data warehouse for easy access in the e-procurement system DA3. We integrate external data with internal e-procurement system to facilitate analysis of procurement TI1. We have explored or adopted parallel computing approaches to big data processing TI2. We have explored or adopted different data visualization tools in our e-procurement system TI3. We have explored or adopted new forms of databases in our e-procurement system TI4. We have explored or adopted cloud-based services for processing data and performing analytics in our e-procurement system TI5. We have explored or adopted open-source e-procurement software for big data analytics
Data-driven Culture (DDC)	Jeble *et al.* (2018)		DD1. Our procurement department treat data as a tangible asset DD2. In our procurement department we base our procurement decisions on data rather than instinct DD3. We are willing to override our own intuition when data contradict our viewpoint on procurement decisions

References

Adjei-Bamfo, P., Maloreh-Nyamekye, T., and Ahenkan, A. (2019). The role of e-government in sustainable public procurement in developing countries: A systematic literature review. Resources, Conservation and Recycling, 142, 189-203. doi: 10.1016/j.resconrec.2018.12.001.

Akter, S., Wamba, S.F., 2016. Big data analytics in e-commerce: A systematic review and agenda for future research. Electronic Markets 26 (2), 173–194. https://doi.org/10.1007/s12525-016-0219-0.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018.

Albawaba. (2015). UAE joins two vital UN networks to promote green procurement and eco-labeling. Retrieved from https://www.albawaba.com/business/pr/uae-joins-two-vital-un-networks-promote-green-procurement-and-eco-labeling-755932.

Allal-Chérif, O. (2010, 2010). How IS contribute to the development of a sustainable procurement policy. Paper presented at the Working Conference on Virtual Enterprises,, Berlin, Heidelberg.

Anitha, P., Patil, M.M., 2018. A review on data analytics for supply chain management: A case study. International Journal of Information Engineering and Electronic Business 11 (5), 30. https://doi.org/10.5815/ijieeb.2018.05.05.

Antonakis, J., House, R.J., 2014. Instrumental leadership: Measurement and extension of transformational–transactional leadership theory. The Leadership Quarterly 25 (4), 746–771. https://doi.org/10.1016/j.leaqua.2014.04.005.

Arifiani, L., Budiastuti, I.D., Erika, W.K, 2019. The effect of disruption technology, and the future knowledge management toward service innovation for telecommunication industry 4.0 in Indonesia. International Journal of Engineering and Advanced Technology 8, 247–257. https://doi.org/10.35940/ijeat.F1040.0986S319, 6 Special Issue 3.

Armstrong, J.S., Overton, T.S., 1977. Estimating Nonresponse Bias in Mail Surveys. Journal of Marketing Research 14 (3), 396–402. https://doi.org/10.1177/002224377701400320.

Atat, R., Liu, L., Wu, J., Li, G., Ye, C., Yang, Y, 2018. Big Data Meet Cyber-Physical Systems: A Panoramic Survey. IEEE Access 6, 73603–73636. https://doi.org/10.1109/ACCESS.2018.2878681.

Badrinarayanan, V., Ramachandran, I., Madhavaram, S., 2019. Resource orchestration and dynamic managerial capabilities: focusing on sales managers as effective resource orchestrators. Journal of Personal Selling & Sales Management 39 (1), 23–41.

Barney, J., 1991. Firm resources and sustained competitive advantage. Journal of Management 17 (1), 99–120. https://doi.org/10.1177/014920639101700108.

Barney, J., Hesterly, W., 2010. VRIO framework, strategic management and competitive advantage, 4th ed. Pearson, New Jersey.

Barraclough, R.W., Bishop, J.M., Danicic, S., Nasuto, S.J., Mitchell, R.J., 2012. SpendInsight: Some remarks on deploying an intelligent spend-analysis system. Paper presented at the AISB/IACAP World Congress 2012: 1st Symposium on Nature Inspired Computation and Applications. NICA 2012, Birmingham. Part of Alan Turing Year 2012.

Becker, J.-M., Klein, K., Wetzels, M., 2012. Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. Long range planning 45 (5-6), 359–394.

Brandon-Jones, A., 2006. Perceived e-procurement quality: exploring and measuring the construct. (PhD Doctoral Dissertation). University of Warwick, UK.

Bromiley, P., Rau, D, 2016. Operations management and the resource based view: Another view. Journal of operations management 41, 95–106. https://doi.org/10.1016/j.jom.2015.11.003.

Broomes, V., 2016. Organisational governance and strategic CSR to strengthen local supply chains - Navigating the maze. In: Developments in Corporate Governance and Responsibility, 9. Emerald Group Publishing Ltd, pp. 3–21.

Chan, R.Y.K., He, H., Chan, H.K., Wang, W.Y.C, 2012. Environmental orientation and corporate performance: The mediation mechanism of green supply chain management and moderating effect of competitive intensity. Industrial Marketing Management 41 (4), 621–630. https://doi.org/10.1016/j.indmarman.2012.04.009.

Chersan, I.C., Dumitru, V.F., Gorgan, C., Gorgan, V., 2020. Green Public Procurement in the Academic Literature. The AMFITEATRU ECONOMIC journal 22 (53), 1–82.

Chidambaram, V., Evans, H., Etheredge, K., 2015. Big data: Is the energy industry starting to see real applications? Supply Chain Management Review 19 (1), 62–64. Retrieved from. http://search.ebscohost.com/login.aspx?direct=true&db=bsu&AN=101388010&site=ehost-live.

Chin, W.W., 1998. The partial least squares approach to structural equation modeling. Modern methods for business research 295 (2), 295–336.

Choi, Y., Lee, H., Irani, Z., 2018. Big data-driven fuzzy cognitive map for prioritising IT service procurement in the public sector. Annals of Operations Research 270 (1-2), 75–104. https://doi.org/10.1007/s10479-016-2281-6.

Chopra, A., 2019. AI in Supply Procurement. Paper presented at the 2019 Amity International Conference on Artificial Intelligence. AICAI 2019.

Cui, M., Pan, S.L., 2015. Developing focal capabilities for e-commerce adoption: A resource orchestration perspective. Information & Management 52 (2), 200–209.

Cui, M., Pan, S.L., Newell, S., Cui, L., 2017. Strategy, resource orchestration and e-commerce enabled social innovation in Rural China. The Journal of Strategic Information Systems 26 (1), 3–21.

Dada, A., Staake, T., Fleisch, E., 2010. Reducing environmental impact in procurement by integrating material parameters in information systems: The example of apple sourcing.

Darnall, N., Jolley, G., Handfield, R., 2008. Environmental management systems and green supply chain management: complements for sustainability? Business Strategy and the Environment 17 (1), 30. Retrieved from. http://adezproxy.adu.ac.ae/docview/213770415?accountid=26149.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F., Roubaud, D, 2017. Can big data and predictive analytics improve social and environmental sustainability? Technological forecasting and social change 144, 534–545. https://doi.org/10.1016/j.techfore.2017.06.020.

Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B.T., Douglas, M.A., 2018. Big data and predictive analytics in humanitarian supply chains. The International Journal of Logistics Management 29 (2), 485–512. https://doi.org/10.1108/ijlm-02-2017-0039.

Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: What are they? Strategic management journal 21 (10-11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E.

Estevez, C., Wu, J., 2015. In: Recent advances in green internet of things. Paper presented at the 2015 7th IEEE Latin-American Conference on Communications (LATINCOM).

Ferraris, A., Mazzoleni, A., Devalle, A., Couturier, J., 2019. Big data analytics capabilities and knowledge management: impact on firm performance. Management Decision 57 (8), 1923–1936. https://doi.org/10.1108/MD-07-2018-0825.

Forsyth, C., 2012. For big data analytics there's no such thing as too big. The compelling economics and technology of big data computing. White Paper. Retrieved from. https://www.cisco.com/c/dam/en/us/solutions/data-center-virtualization/big_data_wp.pdf.

Freeman, J., Chen, T, 2015. Green supplier selection using an AHP-Entropy-TOPSIS framework. Supply Chain Management. An International Journal 20 (3), 327–340. https://doi.org/10.1108/SCM-04-2014-0142.

Gandomi, A., Haider, M., 2015. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management 35 (2), 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007.

Gijzen, H., 2013. Development: Big data for a sustainable future. Nature 502 (7469), 38. https://doi.org/10.1038/502038d.

Griggs, D., Smith, M., Gaffney, O., Noble, I., 2013. Sustainable development goals for people and planet. Nature 496 (7441), 305–307. https://doi.org/10.1038/495305a.

Gupta, M., George, J.F, 2016. Toward the development of a big data analytics capability. Information & Management 53 (8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004.

Jr, Hair, F., J., Hult, G.T.M., Ringle, C., Sarstedt, M, 2016. A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications.

Handfield, R., Jeong, S., Choi, T., 2019. Emerging procurement technology: Data analytics and cognitive analytics. International Journal of Physical Distribution and Logistics Management 49 (10), 972–1002. https://doi.org/10.1108/IJPDLM-11-2017-0348.

Hart, S.L., 1995. A natural-resource-based view of the firm. Academy of Management Review 20 (4), 986–1014. https://doi.org/10.5465/amr.1995.9512280033.

Hart, S.L., Dowell, G., 2011. Invited editorial: A natural-resource-based view of the firm: Fifteen years after. Journal of Management 37 (5), 1464–1479. https://doi.org/10.1177/0149206310390219.

Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., Winter, S.G., 2009. Dynamic capabilities: Understanding strategic change in organizations. John Wiley & Sons.

Helfat, C. E., and Peteraf, M. A. (2003). The dynamic resource-based view: Capability lifecycles. Strategic management journal, 24(10), 997-1010. doi:10.1002/smj.332.

Hickey, R., 2018. Big data analytics - The impact on procurement. Retrieved from. https://softco.com/blog/big-data-analytics-procurement/.

Hitt, M.A., Carnes, C.M., Xu, K., 2016. A current view of resource based theory in operations management: A response to Bromiley and Rau. Journal of operations management 41 (10), 107–109.

Hitt, M.A., Duane Ireland, R., Sirmon, D.G., Trahms, C.A, 2011. Strategic entrepreneurship: Creating value for individuals, organizations, and society. Academy of Management Perspectives 25 (2), 57–75. https://doi.org/10.5465/amp.25.2.57.

Hu, L.t., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal 6 (1), 1–55.

Innamorato, T., Prilepok, M., and Schillinger, I. (2017). The era of advanced analytics in procurement has begun | McKinsey. Retrieved from https://www.mckinsey.com/business-functions/operations/our-insights/the-era-of-advanced-analytics-in-procurement-has-begun.

Jaikumar, G., Karpagam, M., Thiyagarajan, S., 2013. Factors influencing corporate environmental performance in India. Indian Journal of Corporate Governance 6 (1), 2–17. https://doi.org/10.1177/0974686220130101.

Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D., Prakash, A., 2018. Impact of big data and predictive analytics capability on supply chain sustainability. The International Journal of Logistics Management 29 (2), 513–538. https://doi.org/10.1108/ijlm-05-2017-0134.

Jiang, Y., Jia, F., Blome, C., Chen, L, 2019. Achieving sustainability in global sourcing: towards a conceptual framework. Supply Chain Management: An International Journal.

Kähkönen, A.-K., Lintukangas, K., Hallikas, J., 2018. Sustainable supply management practices: Making a difference in a firm's sustainability performance. Supply Chain Management. An International Journal 23 (6), 518–530. https://doi.org/10.1108/SCM-01-2018-0036.

Karduck, A.P., Chitlur, S.S., 2016. Data driven decision making for sustainable smart environments. Paper presented at the 11th International Conference on Innovations in Information Technology, IIT 2015.

Khan, M., 2019. Challenges with big data analytics in service supply chains in the UAE. Management Decision 57 (8), 2124–2147. https://doi.org/10.1108/MD-06-2018-0669.

Kline, R.B., 2015. Principles and practice of structural equation modeling. Guilford publications, New York, NY.

Kock, N., 2015. Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. International Journal of e-Collaboration (IJeC) 11 (4), 1–10. https://doi.org/10.4018/ijec.2015100101.

Labrinidis, A., Jagadish, H.V., 2012. Challenges and opportunities with big data. Proc. VLDB Endow. 5 (12), 2032–2033. https://doi.org/10.14778/2367502.2367572.

Large, R.O., Thomsen, C.G., 2011. Drivers of green supply management performance: Evidence from Germany. Journal of Purchasing and Supply Management 17 (3), 176–184.

Lnenicka, M., Komarkova, J., 2019. Big and open linked data analytics ecosystem: Theoretical background and essential elements. Government Information Quarterly 36 (1), 129–144. https://doi.org/10.1016/j.giq.2018.11.004.

Ma, Y., Ping, K., Wu, C., Chen, L., Shi, H., Chong, D, 2019. Artificial Intelligence powered Internet of Things and smart public service. Library Hi Tech. https://doi.org/10.1108/LHT-12-2017-0274.

Manikam, S., Sahibudin, S., Selamat, H., 2017. Big data analytics initiatives using business intelligence maturity model approach in public sector. Advanced Science Letters 23 (5), 4097–4100. https://doi.org/10.1166/asl.2017.8334.

Mason, M.G., 2018. Big data: Explaining its uses to environmental sciences. Retrieved from. https://www.environmentalscience.org/data-science-big-data.

Masoumik, S. M., Abdul-Rashid, S. H., and Olugu, E. U. (2014). Gaining competitive advantage through strategic green supply chain management: From a literature review towards a conceptual model. International Journal of Supply Chain Management, 3(3), 49-58.

McGovern, M. (2014). Big value for procurement in big data. Retrieved from http://www.mypurchasingcenter.com/technology/technologyarticles/big-value-procurement-big-data.

Miao, F., Wang, G., and Jiraporn, P. (2018). Key supplier involvement in IT-enabled operations: When does it lead to improved performance? Industrial Marketing Management, 75, 134-145. doi:10.1016/j.indmarman.2018.05.002.

Mikalef, P., Boura, M., Lekakos, G., Krogstie, J., 2019a. Big data analytics and firm performance: Findings from a mixed-method approach. Journal of Business Research 98, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044.

Mikalef, P., Boura, M., Lekakos, G., Krogstie, J., 2019b. Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management 30 (2), 272–298. https://doi.org/10.1111/1467-8551.12343.

Moretto, A., Ronchi, S., Patrucco, A.S., 2017. Increasing the effectiveness of procurement decisions: The value of big data in the procurement process. International Journal of RF Technologies: Research & Applications 8 (3), 79–103. https://doi.org/10.3233/RFT-171670.

Muñoz-Garcia, C., Vila, J., 2018. Value creation in the international public procurement market: In search of springbok firms. Journal of Business Research 101, 516–521. https://doi.org/10.1016/j.jbusres.2018.12.041.

Nevo, S., Wade, M.R., 2010. The formation and value of IT-enabled resources: Antecedents and consequences of synergistic relationships. MIS Quarterly 34 (1). https://doi.org/10.2307/20721419.

Noci, G., 1997. Designing 'green' vendor rating systems for the assessment of a supplier's environmental performance. European Journal of Purchasing & Supply Management 3 (2), 103–114.

Panayiotou, N.A., Gayialis, S.P., Tatsiopoulos, I.P., 2004. An e-procurement system for governmental purchasing. International Journal of Production Economics 90 (1), 79–102. https://doi.org/10.1016/S0925-5273(03)00103-8.

Peng, M.W., 2001. The resource-based view and international business. Journal of Management 27 (6), 803–829. https://doi.org/10.1016/S0149-2063(01)00124-6.

Prieto, I. M., and Revilla, E. (2006). Learning capability and business performance: A non-financial and financial assessment. The Learning Organization, 13(2), 166-185. doi:10.1108/09696470610645494.

Raghavendran, P.S., Xavier, M.J., Israel, D, 2012. Green purchasing practices: A study of eprocurement in B2B buying in Indian small and medium enterprises. Journal of supply Chain and operations Management 10 (1), 13–23.

Ramkumar, M., Jenamani, M., 2015. Sustainability in supply chain through e-procurement-An assessment framework based on DANP and liberatore score. IEEE Systems Journal 9 (4), 1554–1564. https://doi.org/10.1109/JSYST.2014.2336291.

Ringle, C.M., Sarstedt, M., Straub, D.W., 2012. Editor's Comments: A Critical Look at the Use of PLS-SEM in" MIS Quarterly". MIS Quarterly iii-xiv.

Rojo Gallego Burin, A., Perez-Arostegui, M.N., Llorens-Montes, J., 2020. Ambidexterity and IT competence can improve supply chain flexibility? A resource orchestration approach. Journal of Purchasing and Supply Management 26 (2). https://doi.org/10.1016/j.pursup.2020.100610.

Ruehle, K., 2018. Procurement: The forgotten element of digital transformation? Manufacturing Business Technology. Retrieved from http://adezproxy.adu.ac.ae/docview/2007710380?accountid=26149.

Sanders, N.R., 2014. Big data driven supply chain management: A framework for implementing analytics and turning information into intelligence. Pearson Education, USA. New Jersey.

Sarstedt, M., Hair Jr, J.F., Cheah, J.-H., Becker, J.-M., Ringle, C.M, 2019. How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australasian Marketing Journal (AMJ) 27 (3), 197–211.

Sarstedt, M., Ringle, C.M., Cheah, J.-H., Ting, H., Moisescu, O.I., Radomir, L., 2020. Structural model robustness checks in PLS-SEM. Tourism Economics 26 (4), 531–554. https://doi.org/10.1177/1354816618823921.
Shokouhyar, S., Seddigh Mohammad, R., Panahifar, F., 2020. Impact of big data analytics capabilities on supply chain sustainability: A case study of Iran. World Journal of Science, Technology and Sustainable Development 17 (1), 33–57. https://doi.org/10.1108/WJSTSD-06-2019-0031.
Singh, S.K., Del Giudice, M., 2019. Big data analytics, dynamic capabilities and firm performance. Management Decision.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., 2007. Managing Firm Resources in Dynamic Environments to Create Value: Looking Inside the Black Box. Academy of Management Review 32 (1), 273–292. https://doi.org/10.5465/amr.2007.23466005.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., Gilbert, B.A., 2011. Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. Journal of Management 37 (5), 1390–1412. https://doi.org/10.1177/0149206310385695.
Song, M., Fisher, R., and Kwoh, Y. (2019). Technological challenges of green innovation and sustainable resource management with large scale data. Technological forecasting and social change, 144, 361-368. doi:10.1016/j.techfore.2018.07.055.
SpendEdge. (2017). SpendEdge Highlights the Effects of Correlating Big Data and Procurement on Strategic Business Decisions. In.
Talamo, C., Atta, N., 2019. FM services procurement and management: Scenarios of innovation. Springer tacts in civil engineering. Springer, Switzerland, pp. 201–242. Cham.
Teece, D.J.T, 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strategic management journal 28 (13), 1319–1350. https://doi.org/10.1002/smj.640.
Teo, T.S.H., Nishant, R., Goh, M, 2017. Do Shareholders Value Green Information Technology Announcements? Journal of the Association for Information Systems 18 (8), 542–576. Retrieved from. http://adezproxy.adu.ac.ae/docview/1946286798?accountid=26149.
Tippins, M. J., and Sohi, R. S. (2003). IT competency and firm performance: is organizational learning a missing link? Strategic management journal, 24(8), 745-761. doi:10.1002/smj.337.
Townsend, J., Barrett, J., 2015. Exploring the applications of carbon footprinting towards sustainability at a UK university: Reporting and decision making. Journal of Cleaner Production 107, 164–176. https://doi.org/10.1016/j.jclepro.2013.11.004.
UAE Ministry of Climate Change & Environment, 2018. UAE green business toolkit. Abu Dhabi: UAE Minstry of Climate Change & Environment. Retrieved from. https://www.moccae.gov.ae/assets/ea2606f7/uae-green-business-toolkit-2018.aspx.
Victor, V., Maria, F.F, 2018. The era of big data and path towards sustainability. Paper presented at the 31st International Business Information Management Association Conference: Innovation Management and Education Excellence through Vision 2020, IBIMA 2018.
Wahid, F., 2012. The green eProcurement infrastructure in the Indonesian public sector: Its antecedents and impacts on the triple bottom line. Paper presented at the 2012 International Conference in Green and Ubiquitous Technology, GUT 2012.
Wales, W.J., Patel, P.C., Parida, V., Kreiser, P.M., 2013. Nonlinear effects of entrepreneurial orientation on small firm performance: The moderating role of resource orchestration capabilities. Strategic Entrepreneurship Journal 7 (2), 93–121. https://doi.org/10.1002/sej.1153.
Walker, H., Brammer, S., 2012. The relationship between sustainable procurement and e-procurement in the public sector. International Journal of Production Economics 140 (1), 256–268. https://doi.org/10.1016/j.ijpe.2012.01.008.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.-f., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.
Wang, J., Xue, Y., Yang, J, 2020. Boundary-spanning search and firms' green innovation: The moderating role of resource orchestration capability. Business Strategy and the Environment 29 (2), 361–374.
Wong, C.W.Y., Wong, C.Y., Boon-itt, S, 2018. How Does Sustainable Development of Supply Chains Make Firms Lean, Green and Profitable? A Resource Orchestration Perspective. Business Strategy and the Environment 27 (3), 375–388. https://doi.org/10.1002/bse.2004.
Wu, J., Guo, S., Li, J., Zeng, D, 2016a. Big data meet green challenges: Big data toward green applications. IEEE Systems Journal 10 (3), 888–900. https://doi.org/10.1109/JSYST.2016.2550530.
Wu, J., Guo, S., Li, J., Zeng, D, 2016b. Big Data Meet Green Challenges: Greening Big Data. IEEE Systems Journal 10. https://doi.org/10.1109/JSYST.2016.2550538.
Xu, P., Kim, J., 2014. Achieving dynamic capabilities with business intelligence. Paper presented at the Pacific Asia Conference on Information Systems.
Zeng, J., Khan, Z., 2019. Value creation through big data in emerging economies: The role of resource orchestration and entrepreneurial orientation. Management Decision 57 (8), 1818–1838. https://doi.org/10.1108/MD-05-2018-0572.
Zhang, D., Pan, S.L., Yu, J., Liu, W., 2019. Orchestrating big data analytics capability for sustainability: A study of air pollution management in China. Information & Management, 103231. https://doi.org/10.1016/j.im.2019.103231.

Bader K. AlNuaimi is a doctoral candidate at Abu Dhabi University, UAE. He is senior procuremnet manager at a local firm. His research interests are in green procurement behaviors and artificial intelligennce in modern supply chains.

Dr. Mehmood Khan is an associate professor of management at Abu Dhabi University. He has served as the director of the center of excellence in Sustainable Business Processes, at Abu Dhabi University. He holds a BS in Mechanical Engineering; and a PhD in Industrial Engineering from Toronto, Canada. He has taught various courses in Operations Research/Management and Supply Chain Management at King Fahd University, Saudi Arabia; Brock University, Canada; Ryerson University, Canada. His research interests span role of technology; internet of things; quality control and sustainable supply chains. His work has been published in various top ranked journals.

Mian M. Ajmal is currently working as an associate professor of management at the Abu Dhabi University, Abu Dhabi, UAE. He has served as a research fellow at the Industrial Management Department, University of Vaasa, Finland. He holds a PhD in Business Administration and Economics from the University of Vaasa, Finland. He has been involved in several European Union research projects. His research interests pertain to knowledge, project and supply chain management; entrepreneurship, sustainability; and organizational behavior and culture. He has published more than 50 research articles in several internationally well-known journals.