Embracing Big Data Capabilities: Toward Achieving Green E-Procurement in Public Sector

DBA Dissertation

By

Bader K. AlNuaimi

ID# 1063826

Abu Dhabi University

College of Business Administration

Abu Dhabi, UAE

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Bader Khamis AlNuaimi

Approved:

Dr. Mehmood Khan
Associate Professor of Management, College of Business
Abu Dhabi University
Committee Chair

Dr. Mian Ajmal
Associate Professor of Management, Institute/ College
Abu Dhabi University
Committee Member

Professor Barry O'Mahony
Dean, College of Business
Abu Dhabi University

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Abstract

Public procurements can be instrumental in enhancing sustainable development worldwide by advancing green procurement, as they are a substantial element in many countries' national economies. Due to the recent development of e-procurement (EP) platforms, governments and suppliers can now easily and transparently interact with each other to construct, disseminate, and pilot green public procurement (GPP) policies and improve environmental performance (ENP). However, there are many types of EP platforms, and not all of them provide the flexibility necessary for the efficient integration of GPP. For this reason, recent studies suggest that the next set of improvements in EP systems should enable the integration of operational data and the adoption of big data technology. The emerging big data technology and concepts can offer public procurement with a range of benefits—such as simplifying life cycle assessment, spend analysis, and transparency. Recent studies in big data analytics capabilities (BDAC) have shown that it has the potential to transform and innovate the traditional EP system into green EP.

Although big data technology has become more available for organizations, big data can be of limited value if the decision maker and employees within an organization are unable to understand the big data analysis. Hence, the aim of this study was to contribute to the literature related to resource-based view (RBV) theory, natural-resource-based view (NRBV) theory, and the dynamic capability (DC) framework, particularly regarding the adoption of big data technology to achieve GPP. Drawing upon this theoretical foundation, the purpose of this study was twofold: (1) to examine the relationships among the BDAC, specifically technological

capabilities (TC) and human capabilities (HC) and EP under the moderating effect of a data-driven culture (DDC); and (2) to identify what, if any, direct and indirect effects the TC and HC have on ENP under the mediation influence of EP.

The study used a constructive positivism quantitative research method by sending out a carefully developed questionnaire survey to a sample group consisting of procurement professionals from the United Arab Emirates (UAE) government sector. After a promising pilot study was completed, the data was then collected from 216 participants. IBM SPSS was used to perform regression analysis of the relationship between the variables to test and verify the research hypotheses. In addition, Hayes PROCESS SPSS macro was used for moderation and mediation testing.

The primary results determined that TC and HC have a significant influence on EP. However, DDC does not have a significant moderation effect on the relationship between both big data capabilities (TC and HC) and EP. The findings also determined that EP has a positive influence on ENP, and when EP was introduced as a mediator between the relationship of TC and ENP, ENP improved even further. However, EP has no mediation effect on the relationship between TC and ENP.

This study has several theoretical implications. Most importantly, it is among the first studies to assess the impact of big data capabilities (TC and HC) on ENP and EP and to evaluate the moderation impact of DDC on the relationship between big data capabilities and EP. In addition, the study utilized the DC framework to view the construct of big data capabilities as multidimensional, which integrates the technical, human, and cultural perspectives instead of viewing big data capabilities as a technical construct. Lastly, it contributes to the emerging literature on big data by advancing the theoretical understanding of BDAC in relation to ICT-based procurement and environmental science via the DC framework.

This study offers many practical contributions. Public organizations that aim to implement big data in their procurement function must focus on assuring the interoperability of data infrastructure with other systems and applications and the availability of accessible data for analysis. At the same time, organizations must focus on training management and employees on data technology, analysis, and developing technical and relational knowledge to develop skilled procurement analysts. Overall, this study's findings offer a more advanced understanding of the impact of big data capabilities on EP, thereby addressing the crucial questions of how and when these capabilities can enhance environmental sustainability in procurement and supply chains.

The study limitations were linked to four major areas associated with the limited sample size and scope of the study in terms of constructs and country setting, in addition to the limitation due to the use of a cross-sectional research design for data collection.

Keywords: big data, green procurement, e-procurement, sustainable development, United Arab Emirates.

Declaration

I hereby declare that:

- The dissertation has been solely constructed, composed, and produced by the candidate. No other person's work has been used without due acknowledgment and full reference in the main text of the dissertation.
- The dissertation has not been submitted by any means for the award of any academic or professional degree or diploma in any other institute or university.
- All research procedures reported in the dissertation were approved by ADU institutional review board.
- All respondents were given the consent form and have been assured anonymity with no link reference to their personal or organizational identities.

Abbreviations

ADU: Abu Dhabi University

AI: Artificial Intelligence

BDA: Big Data Analytics

BDAC: Big data Analytics Capabilities

BI&A: Business Intelligence and Analytics

DC: Dynamic Capability framework

DDC: Data-driven culture

ENP: Environmental Performance

EP: E-procurement

GDP: Growth Domestic Products

GP: Green Procurement

GPP: Green public procurement

GSCM: Green Supply Chain Management

HC: Human Capabilities

ICT: Information and Communication Technology

IoT: Internet of Things

LCA: Life Cycle Assessment

MoF: United Arab Emirates Ministry of Finance

NGO: Nongovernmental Organizations

NRBV: Natural-resource-based View Theory

RBV: Resource-based View Theory

SCM: Supply Chain Management

TC: Technological Capabilities

TCO: Total Cost of Ownership

UAE: United Arab Emirates

VRIN: (Valuable, Rare, Imperfectly imitable, Non-substitutable) resources

Acknowledgment

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CHAPTER I. INTRODUCTION

1.1 Foundation of the Study

Public procurements can be instrumental in enhancing sustainable development around the world, as they are a substantial element in many countries' national economies (Brammer and Walker, 2011; Fisher, 2013). The public sector can influence green procurement (GP) by both designing suitable policies and leveraging "green" markets through the significant power of public procurement. As a result, green public procurement (GPP) has emerged as a key player in changing unsustainable consumption and production outcomes, and, indeed, it is increasingly used (Cheng *et al.*, 2018). Through the recent development of e-procurement (EP) platforms, governments and suppliers can easily and transparently interact with each other to obtain information about products, technologies, and legislation. For this reason, it has been recommended that organizations use EP platforms to construct, disseminate, and pilot GPP policies and improve environmental performance (Allal-Chérif, 2010). Consequently, to be effective at GPP, governments' EP systems should integrate information related to green products and services. In doing so, purchasing officers' search costs for alternative green products can be reduced, which may incentivize green purchasing behavior. Such systems can also create standard requirements in favor of GPP and methods by which governments can track their green product spending and achieve better environmental performance (Darnall, Nicole *et al.*, 2017).

With the recent emergence of big data technology, improving environmental performance (ENP) is becoming more realizable; because big data involves not only an information explosion but also a technological explosion, as the values generated from a massive amount of data must be able to be collected, shared, and analyzed to facilitate better decision making. Hence, public organizations can implement many ENP enablers to improve their monitoring and control processes, using the emerging capabilities of big data (Dubey *et al.*, 2017; Talamo and Atta, 2019).

The government of the United Arab Emirates (UAE) has consistently endeavored to enhance the sustainability of its economy and promote a green economy (Vcantugakkas and Yapin, 2017). The Ministry of Climate Change and Environment in the UAE has focused on GPP in collaboration with relevant agencies to tackle climate change issues in a way that is both economically logical and protective of natural resources (Aamir, 2017). This is in line with the fact that the total government spending in the UAE accounts for roughly 24% of its gross domestic product, which offers insight into the expectation that government purchases of green products and services would drive the market toward a green economy (Oxford Business Group, 2018). However, the UAE government is still facing serious challenges in implementing GP, as evidenced by the country's struggle to move up in the global sustainability rankings in the category "environmental well-being" (RobecoSAM, 2018; Sustainable Development Solution Network, 2017; Sustainable Society Index, 2018), as demonstrated in Table 1-1. Such reports are alarming to policymakers and academics in the UAE and raise the question of whether the efforts made by the UAE government in terms of policy changes and adopting global best practices in the government sectors are enough to implement GPP successfully and drive sustainability and a green economy.

Table 1- 1 UAE sustainability ranking on Social Society Index from 2006 to 2016

Year	2006	2008	2010	2012	2014	2016
Human Well-being	81	82	88	92	90	48

Environmental Well-being	154	152	150	151	150	152
Economic Well-being	25	27	28	26	11	10

Moreover, the UAE government has also aimed to be ahead of other governments in achieving high efficiency and excellence in its public services. The UAE’s economic diversification vision entails the use of some of the latest technologies and innovations, as it aims to be at the forefront of global competitiveness (Zaatari, 2019). In 2018, the World Digital Competitiveness Yearbook ranked the UAE as the 17th most digitally competitive nation and as 5th in the use of big data and analytics (IMD World Competitiveness Center, 2018). The UAE has successfully implemented e-government services and transformed them into mobile government (smart/m-government) platforms. Most recently, the UAE has shifted to artificial intelligence (AI)–enabled services, which necessitated the establishment of the Ministry of AI (Halaweh, 2018). This indicates that the UAE government is at the forefront of technology adoption, and, naturally, the utilization of big data by public and private sectors is happening more and more (D'Mello, 2018). However, a recent study on big data implementation in the UAE suggested that there are still many significant technical, operational, cultural, organizational, and procedural challenges to deploying big data in the UAE supply chain (Khan, 2019). Furthermore, UAE organizations have yet to make a breakthrough in integrating the capabilities of big data in procurement platforms (Mathew, 2019), creating a significant challenge to improving ENP in the UAE public sector.

1.2 Statement of the problem

The implementation of GPP, although necessary, is an extremely challenging task (Klassen and Johnson, 2004). It is also unrealistic to expect public officers, managers, and procurers to adopt sustainable procurement practices in the absence of the appropriate information and tools; this makes it essential to ensure that procurers and staff receive substantial training regarding the technical and legal aspects of GPP implementation and the concept of lifecycle costs (Darnall, N. *et al.*, 2008). In addition, implementing GPP in EP platforms goes beyond simply transferring GPP procedures to EP tools. Instead, it requires the streamlining of various pre-award and post-award phases and the integration of ENP data and feedback to make these processes simpler and making GPP more manageable (Muñoz-Garcia and Vila, 2018).

Currently, there are many types of EP platforms, and not all of them provide the flexibility necessary for the efficient integration of GPP. Procurement decisions in the public sector rarely incorporate actual and up-to-date field data and performance feedback relating to the procured parts, and the inherent life cycle of products and the limitations of traditionally available EP platforms often result in the acquired information not being used (Chidambaram *et al.*, 2015). Without actual data and feedback on performance, the procurement functions are not armed with the critical total cost of ownership (TCO)–type input to make a holistic green product selection. For this reason, it was suggested in recent studies that the next set of improvements in EP systems should be allowing the integration of operational data and the adoption of a data-driven mindset (Chidambaram *et al.*, 2015; Ruehle, 2018). Yet, during the “Big Data” and “Industry 4.0” revolutions of recent years, organizations have increasingly looked to technologies such as cloud computing, big data analytics (BDA), 3D printing, and robotics to renovate 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, by leveraging big data concepts, procurement functions can quickly gather more information and collaborate with other functions within the organization to make more informed green procurement decisions across the product lifecycle (Chidambaram *et al.*, 2015). As a result of this potential, there have been increasing calls for more big data to help secure a sustainable future (Griggs *et al.*, 2013).

1.3 Purpose of the study

Emerging studies in big data have shown that deploying digital tools can make public spending more transparent and evidence-oriented; this offers a range of benefits—including significant savings for all parties, simplified and faster processes, reductions in red-tape and administrative burdens, increased transparency, more considerable innovation, and new business opportunities—by improving the ability of businesses to access cross-border public procurement markets (Muñoz-Garcia and Vila, 2018). Although big data technology has become more available for public organizations, big data can be of limited value if the decision-maker and employees within an organization are unable to understand the big data analysis (Labrinidis and Jagadish, 2012). In fact, it has been argued that obtaining data and conducting proper BDA are not the biggest obstacles in big data but rather that the adoption barriers are primarily related to managerial and cultural change (LaValle *et al.*, 2011). 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 study suggests that if governments embrace some of the capabilities offered by big data within its EP functions, it will help make the dream of achieving green EP realizable.

Hence, this study aimed to contribute to the literature related to resource-based view (RBV) theory, natural-resource-based view (NRBV) theory, and the dynamic capability framework (DC), particularly regarding the adoption of big data technology to achieve GPP. Drawing upon this theoretical foundation, the purpose of this study was twofold: (1) to examine the relationships among the big data capabilities, specifically; technological capabilities (TC) and human capabilities (HC), and EP under the moderating effect of a data-driven culture (DDC); and (2) to identify what, if any, direct and indirect effects the capabilities of big data of TC and HC have on ENP under the mediation influence of EP.

1.4 Nature of study

This study is an exploration of ENP in government organizations. The research approach used was a constructive positivism quantitative research method, as it was believed to offer a more clinical outcome to the research, building on the recommendations of Lakshman *et al.* (2000), who argued that this approach offers a more detailed research output. The quantitative approach assumes that meaningful social research should be based on the physical observation of research-associated phenomena, as this helps to facilitate the examination of the strength of the associations between quantified constructs (Howell, 2012). This is followed by the collection of such observations and their subsequent analysis and validation with the help of acknowledged and established methods for the selection of samples, analysis of data, and validation of findings, thus providing a more scientific response to the research that ensures the study will hold up throughout the academic peer review process (Saunder *et al.*, 2009).

The variables of interest in this study were gathered in a numerical format using validated survey instruments from the available literature. This study involved the use of a survey instrument to facilitate the data collection process. It is intended to assess the presence and impact of the relationships among the independent variables, moderated variable, mediated variable, and dependent variable, to provide a measurement that was also analyzed as part of this research dissertation.

1.5 Research questions and hypotheses

The purpose of this quantitative study was to examine the relationships among the big data capabilities (TC and HC) on EP under the moderating effect of a DDC, as well as the influence of these capabilities on ENP under the mediation influence of ENP. The focus of the study was ENP as an independent variable and the big data capabilities of TC and HC as dependent variables; EP as a dependent variable to TC and HC and as a mediated variable to ENP; and DDC as a moderated variable to EP. To achieve these objectives, after an extensive review of the literature, this study used a variety of theoretical frameworks have—including the RBV, NRBV, and DC—and formulated the following research questions and hypotheses:

***RQ1.* What is the influence of big data capabilities (technological and human capabilities) on UAE public organizations' e-procurement?**

Hypothesis 1 *(H1).* The technological capabilities of big data have a positive relationship with e-procurement performance.

Hypothesis 2 *(H2).* The human capabilities of big data have a positive relationship with e-procurement performance.

***RQ2.* What is the impact of a data-driven culture on the relationship between big data capabilities (technological and human capabilities) and e-procurement?**

Hypothesis 3 *(H3).* A data-driven culture positively moderates the relationship between technological capabilities and e-procurement performance.

Hypothesis 4 *(H4).* A data-driven culture positively moderates the relationship between human capabilities and e-procurement performance.

***RQ3.* What is the relationship between e-procurement and environmental performance in the UAE public sector?**

Hypothesis 5 *(H5).* E-procurement has a positive influence on organizations' environmental performance.

***RQ4.* What is the influence of e-procurement on the relationship between big data capabilities (i.e., technological and human capabilities) and environmental performance in the UAE public sector?**

Hypothesis 6 *(H6).* Technological capabilities under the mediation effect of e-procurement have an influence on environmental performance.

Hypothesis 7 *(H7).* Human capabilities under the mediation effect of e-procurement have an influence on environmental performance.

Figure 1 illustrates the relationships between the dependent, independent, moderating, and mediating variables used in this study.

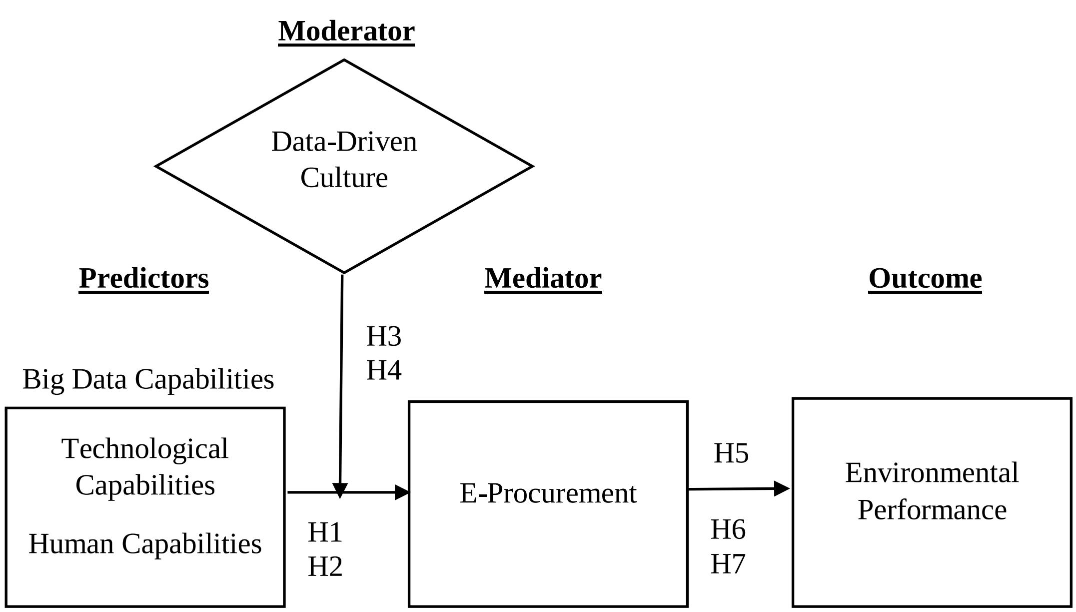


Figure 1. 1 Research model

1.6 Definition of key terms

Environmental Sustainability refers to an organization's ability to maintain environmental safety and minimize resource utilization; hence, sustainable organizations must be capable of reducing costs and preventing environmental problems to ensure a clean and green atmosphere (Vinodh, 2011).

Green procurement is the acquisition of products or services that have a lower impact on the environment over their whole lifecycle in comparison to their typical equivalents. It includes the integration of environmental concerns into purchasing decisions based on price, performance, and quality (Lacroix, 2008).

Green public procurement (GPP) is the process whereby public entities procure goods, services, and works that have a reduced environmental impact throughout their lifecycle (Cheng *et al.*, 2018).

E-procurement is the use of Internet-based (integrated) information and communication technology (ICT) 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).

Big data is a vast term referring to huge or complex data sets, for which working with conventional data processing applications is insufficient (Wu *et al.*, 2016).

Data management includes the processes and supporting technologies needed to acquire and store data, as well as to retrieve and prepare it for analysis (Labrinidis and Jagadish, 2012).

Big data analytics refers to techniques used to analyze and acquire intelligence from big data. It is a subprocess in the overall process of insight extraction from big data (Labrinidis and Jagadish, 2012).

Dynamic capabilities is a term composed of two parts: while *dynamic* is identified as having the ability to renew competences to achieve congruence with a changing business environment, *capabilities* are key roles of strategic management in appropriately adapting, integrating, and reconfiguring external and internal organizational skills, functional competencies, and resources to match the requirements of a changing environment (Teece *et al.*, 1997).

Green capabilities refer to the ability of an organization to apply its existing resources and knowledge to create and enhance environmental performance to respond to a dynamic market (Chen, Y. and Chang, 2013).

Technological capabilities refer to a firm's "abilities to mobilize and deploy IT-based resources in combination or co-presence with other resources and capabilities" (Bharadwaj, 2000, p. 171).

Human resources involve an organization's employees' knowledge, experience, problem-solving abilities, leadership qualities, business acumen, and relationships with others (Barney, 1991).

Human capabilities are the skills required of an organization's employees to work in a big data environment; these have been suggested to be based on two constructs pertaining to the respective type of skills: technical and managerial skills (Mikalef *et al.*, 2019a).

Technical skills are the know-how necessary to use novel forms of technology to obtain intelligence from big data; they reflect the level to which employees have the appropriate skills to achieve their jobs effectively in the context of BDA (Gupta and George, 2016; Mikalef *et al.*, 2019a).

Managerial skills refer to the degree to which managers are knowledgeable about BDA-related areas and can apply them in practice, as well as how well managers understand the business needs of different functional areas and opportunities in relation to BDA (Chen, Y. S. and Lin, 2015).

Data-driven culture is an intangible resource, fundamental to other dynamic capabilities that must be embedded in businesses' routines related to BDA-driven decision making (Arunachalam *et al.*, 2018).

1.7 Significance of the study

This study aims to fill a gap in the literature on sustainable development by investigating the influence of emerging big data capabilities on EP to improve GPP and ENP in the public sector as research on integration of the these constructs is scant as you will discussed the next chapter. This study also recognized that the concepts of GPP and big data are relatively new in the UAE, so knowledge and experience in this area are possibly lacking, which could present a challenge. However, the outcome of this study has many contributions, including addressing the lack of studies about ENP and big data in the UAE and adding to the topical body of work. The findings of this study are useful for academics and practitioners of big data and GPP in the UAE, specifically regarding how well prepared the country is for the greater reforms and structural changes that lie ahead.

1.8 Assumptions

There were four assumptions associated with this study. The first assumption was that all the targeted public organizations were practicing GPP. The basis of this assumption was recent reports and studies that suggested the UAE is utilizing public procurement to tackle climate-change issues in a way that is both economically logical and protective of natural resources

(Aamir, 2017; Vcantugakkas and Yapin, 2017). The second assumption was all the target public organizations were either currently deploying big data in their procurement function or were starting to do so. This assumption was appropriate because recent reports suggested the UAE has launched new initiatives to employ AI tools in government operations with the aim of enabling governments and companies to make their procurement processes more efficient and transparent by employing a multi-stakeholder approach (Emirates News Agency, 2019). Furthermore, the UAE Ministry of Finance (MoF) developed an Oracle system for EP that aims to increase efficiency and speed up the work process in the MoF or in other ministries and federal entities (UAE Government Portal, 2019b).

The third assumption was that the population sample was representative of the public organizations in the UAE. The quest for a representative sample when conducting a survey is a common one; according to Bryman (2016), samples should be selected on the basis of their appropriateness to the purposes of the investigation and according to principles related to finding a sample that can represent—and therefore act as a microcosm of—a wider population. A power analysis was conducted in this study and revealed that a minimum of 129 participants were required to achieve statistically significant results. Thus, to improve the population representation, generalizability, and power of the test, this study set out to select a sample size of 580 participants. The fourth assumption was that participants would respond in an honest and truthful manner. Bryman (2016) asserted that surveys should be designed to encourage participants to respond honestly, without any fear of consequences. As such, this study used appropriate measures to protect participants' anonymity and confidentiality and to allow participants to withdraw from the survey at any time they wish.

1.9 Limitations

Limitations are the weaknesses of a study that may affect its outcomes, and this study faced a few. First, as with other empirical studies, the results may not be typical for populations that exist outside the boundaries of the sample. This study determined that the subjects would be limited to employees with enough knowledge about the phenomenon under study—that is, big data practices and EP in the UAE public sector. Obtaining permission from the public sector or government would have been too difficult and time-consuming to undertake in this research; thus, a combination of key informants in public organizations and personal contacts have been triggered to invite employees that fit the requirements to participate in the study. Finally, this study was limited to the independent variables of TC and HC, the mediating variable of EP, the moderating variable of DDC, and the dependent variable of ENP.

1.10 Organization of the remainder of the study

This dissertation is divided into six chapters. Chapter 1 included an introduction to the study, an outlining of the problem and purpose statements, the research questions, and other key introductory information. In Chapter 2, extensive literature related to this study is reviewed, leading to an identification of the gaps in the literature. Chapter 3 then details relevant information about RBV theory, NRBV theory, and DC, leading to the development of propositions and the theoretical framework used in this study. The research methodology is discussed in Chapter 4, including the research design, sampling procedures, instrumentation/measures, pilot study, data analysis, and ethical considerations. Chapter 5 presents and describes the data results. Finally, Chapter 6 provides a discussion of the results, implications, limitations, and potential avenues for future research.

CHAPTER II. LITERATURE REVIEW

The purpose of this study is to examine some of the inherent big data capabilities required to improve organizations' environmental performance (ENP) in public procurement. The following research questions guided the study: (1) What is the influence of big data capabilities specifically; technological capabilities (TC) and human capabilities (HC) on e-procurement (EP) performance? (2) What is the impact of a data-driven culture (DDC) on the relationship between big data capabilities (TC and HC) and EP performance in public sector? (3) What is the relationship between EP and ENP in public sector? And (4) what is the influence of EP on the relationship between big data capabilities (TC and HC) and ENP in public sector? Consequently, this chapter aims to outline the concept of ENP, EP, big data, big data capabilities, then it shall take a deep dive in the previous literature to explore the role of EP in improving ENP from big data perspective. The chapter closes with a summary of the literature review and the main findings.

2.1 Search method

Technology, innovation, and green procurement (GP) have been investigated in recent years as emerging capabilities required to achieve high-quality ENP (Chuang and Huang, 2018; Reyes-Santiago *et al.*, 2019). However, before exploring the literature in detail, we attempted to produce an overview of the published work on the topic under study; thus, the SCOPUS database was used to search for literature on the topic published from 2000 to 2019, and then tabulated and analyzed on the related topic from the last 20 years using Biblioshiny Web application [http://www.bibliometrix.org (Massimo and Corrado, 2017)]. The results revealed 722 publications that discussed "big data" and "sustainable development". The most frequently occurring keywords were *sustainability*, *big data analytics*, and *cloud computing*. We next searched for publications that discussed "big data", "government sector" and "public sector", and the results showed 224 publications on that topic. The most frequently occurring keywords were *decision-making*, *information management*, and *government data processing*. Moreover, when the search was narrowed down to publications that discussed "big data" and "environmental performance", 19 publications dated between 2013 and 2019 were found, which indicates a lack of research in this area. In fact, when this search looked for publications that discussed "big data" and "e-procurement", only five publications discussed this topic, between 2012 and 2019.

These results show a shortage of published works related to this study topic. There exists a definite gap in the established research that demands attention to combine all three constructs under big data concept. Due to this lack of research about big data's role in improving EP operations in the area of ENP, a research gap is determined by focusing on the stream in literature that examines big data capabilities' role in improving ENP in the public sector, along with the influence of EP (see Figure 2.1).

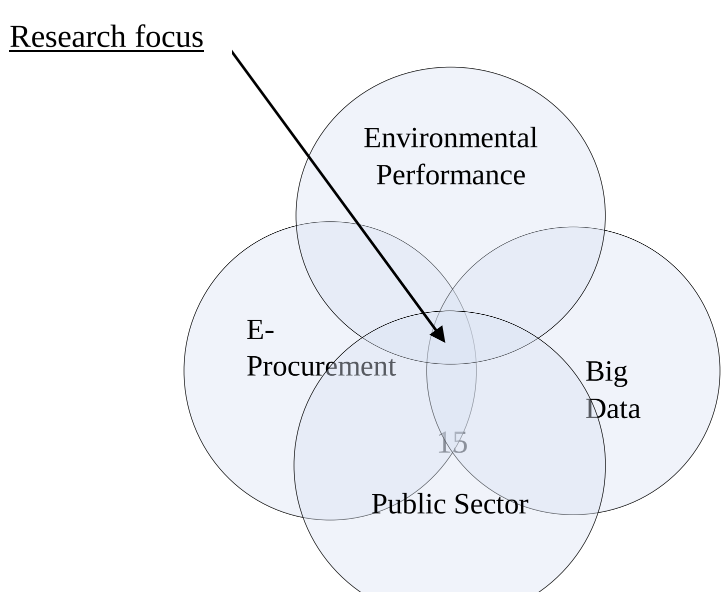


Figure 2. 1 Research focus of this literature review

2.2 Environmental performance related literature

2.2.1 Overview of the concept of environmental performance

The literature reviewed related to ENP demonstrated a high level of interest and research in many sectors. Currently, ENP has many indicators, including the control of harmful waste, such as carbon monoxide emissions, wastewater, and solid waste. Although no common measure exists for judging how green an organization is, over the past three decades, some tools have been developed and are being continuously improved to achieve and measure organizations' ENP, which we shall describe and summarize in the next few paragraphs.

One of the earliest attempt to understand ENP of organizations was Maimon (1994), who suggested a three-stage approach to analyze organization's ENP. The first stage involves a company's adaptation to the market's regulations and demands, such as employing pollution control equipment in output lines, without changing the production structure or final product. In the second stage, in the organization modifies existing processes or products (including packaging) to prevent pollution and problems that undermine the achievement of its business strategy. The last stage is highlighted by a business' anticipation of further environmental problems that may occur—that is, adopting proactive behaviors and seeking ecological excellence (Maimon, 1994). Many years later, 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 green procurement policy, and (h) involvement of the company in local community activities (Jaikumar *et al.*, 2013). More recently, International Organization for Standardization (ISO) 14000 certification was found to be somewhat successful in integrating organizational resources, structure, and environmental practice data to overcome environmental issues (Beske and Seuring, 2014). However, other academics have suggested that a commitment to ENP, an environmental policy, and the implementation of ISO 14000 are not enough to achieve satisfactory ENP but that it requires other enablers (i.e., competencies) such as those summarized in Table 2-1.

Table 2- 1 Key enablers to achieve environmental performance

Key enablers to achieving environmental performance	**Sources**
Concrete environmental action plan in areas such as energy saving, air pollution control, and waste management	Dada *et al.* (2010); Jaikumar *et al.* (2013); Townsend and Barrett (2015)
Environmental education and awareness program	Jaikumar *et al.* (2013)
Giving priority to environmental impact in the selection of new technology	Dastbaz *et al.* (2015); Godbole and Lamb (2015); Jaikumar *et al.* (2013); Wong and Zhou (2015)

Conducting life cycle analysis study on products	Appolloni *et al.* (2014); Dada *et al.* (2010); Jaikumar *et al.* (2013); Mendoza *et al.* (2014); Wong and Zhou (2015),
Monitoring and reporting of environmental information and data	Broomes (2016); Jaikumar *et al.* (2013); Kähkönen *et al.* (2018); Townsend and Barrett (2015)
Practice of environmental accounting	Barraclough *et al.* (2012); Beske and Seuring (2014); Broomes (2016); Jaikumar *et al.* (2013)
Green supply chain management (GSCM) and supply relationship	Freeman and Chen (2015); Jaikumar *et al.* (2013); Kähkönen *et al.* (2018); Narasimham *et al.* (2013); Reuter *et al.* (2010); Uttam and Roos (2015)
Green procurement and involvement of the company in local community activities	Freeman and Chen (2015); Jaikumar *et al.* (2013); Reuter *et al.* (2010); Shi, P. *et al.* (2015); Uttam and Roos (2015)
Practice of environmental decision making	Broomes (2016); Freeman and Chen (2015); Shi, P. *et al.* (2015); Townsend and Barrett (2015)

2.1.2 Role of green procurement in improving environmental performance

The ENP enablers presented in Table 2-1 show that green procurement is obviously a key enabler for improving organizations' ENP. *Green procurement* (GP) is defined by Lacroix (2008) as the acquisition of products or services that have a lower impact on the environment over their whole lifecycle than do their typical equivalents. It includes the integration of environmental concerns into purchasing decisions based on price, performance, and quality. Similarly, *green public procurement* (*GPP)* is defined as the process whereby public entities procure goods, services, and works that have a reduced environmental impact throughout their lifecycle (Cheng *et al.*, 2018). In general, GP preferences are the environmental requirements that a product needs to fulfill during its performance of work or service. Thus, environmental procurement preferences are formulated as criteria for the awarding of a contract, applied in the evaluation of a tender alongside other criteria for achieving ENP (Lacroix, 2008; Varnäs, 2008).

In the past ten years, many studies investigated how implementing GP impacts ENP from different perspectives. For example, Large and Thomsen (2011) concluded that the practice of GP by green supplier assessment and green collaboration will improve not only procurement performance but as well its ENP. Further, Chan *et al.* (2012) looked at GP practices through the lens of green supply chain management (GSCM) and determined that GP practices will improve corporate performance and lead to improved ENP. Other studies have evaluated the impact of green products vs green practices on ENP, and determined that both product-based and process-based GP does not only have a positive effect on ENP, but also improve a firm's overall organizational performance (Song, H. *et al.*, 2017a).

In general, awareness of the importance of environmental sustainability has been growing over the last few decades, and the overwhelming majority of policymakers, nongovernmental organizations (NGOs), and individuals have been pushing organizations across the world to engage in diverse types of sustainability practices in an attempt to bring about environmental protection and increase organizations' ENP (McCarthy, 2014). It has been well established in the literature that GP will lead to better ENP globally and allow organizations to achieve competitive advantages (for examples, see the following: (Chiou *et al.*, 2011; Dubey *et al.*, 2013; Dubey *et al.*, 2015; Eltayeb *et al.*, 2011; Jaikumar *et al.*, 2013; Reuter *et al.*, 2010; Shi, P. *et al.*, 2015; Uttam and Roos, 2015)).

2.1.3 Environmental performance in the public sector

The literature reviewed revealed that there are some differences between private and public sectors when it comes to achieving ENP. The public sector is less studied then the private sector, yet they all agreed that achieving ENP in the public sector is more challenging. The first main difference is motivation. In general, private organizations are ideally brought to account by the demands of corporate legislation, competitive market forces, and the influence of shareholders, but in the public sector, these forces may be absent (Burritt and Welch, 1997). When it comes to public organizations, the idea of ENP could be relate to the area liability: the acts made on behalf of organizations and the effects of its consequences on ecological systems (Burritt and Welch, 1997). Another main difference between private and public sector is stakeholder interest. Public sector has multiple stakeholders, which complicates how public organizations must deal with ENP. Burritt and Welch (1997) suggested that five key stakeholder groups seem to have a specific interest in ENP in the public sector: (a) the regulators, (b) the agencies of parliament, (c) those who take on an activity that has environmental consequences, such as managers, industry groups, and natural resource planners, (d) those who are affected by those acts, such as local and international communities, and (e) NGOs and other specific community interest groups. Therefore, ENP implementation in governments may not be achievable without all stakeholders being presented with the actual and potential ENP informations (Burritt and Welch, 1997; Greiling *et al.*, 2015). The third main difference between public and private ENP is the difference in accounting practices. In general, private sector have more advance accounting systems then the public sector, and public entities needs years to catch up with the private sector. Accounting information systems play an crucial role in leading and supporting the managerial, organizational, and cultural changes stemming from the acceptance of environmental responsibility; they could do this by providing information that allows for the evaluation of the organizations' ENP (Monteiro and Ribeiro, 2017). Lastly, measuring ENP in the public sector is complicated and challenging more than the private sector, as it depends on many factors, such as national gross domestic product (GDP), type of government (i.e., democratic or autocratic), transparency, corruption, rule of law, and effective governance (Fiorino, 2011).

The good news is that many of the key ENP enablers suggested in previous work—such as the practice of environmental accounting, green supply chain management (GSCM), and GPP implementation—can be achieved with the availability of a large unstructured dataset that can be analyzed to assist in practicing environmental decision making. Hence, the findings in this study can direct research gaps in these areas to proper recommendations. In addition, though this area of research has been under investigation for a while, there is an evident lack of research that seeks to understand the basic level of ENP and GPP in the UAE context. Thus, because the current study was conducted in a developing country (i.e., the UAE), its results should be of great value to the UAE government, similar governments around the globe by providing recommendations about how to improve ENP in the public sector.

2.1.4 ICT's Influence on environmental performance

Nowadays, information and communications technology (ICT) is a pillar of the corporate and government activity used to improve organizational performance because of its embodiment of competitive advantage through its optimization of processes, introduction of a high-performance technological watch function, and improvement of overall performance (Allal-Chérif, 2010). In fact, ICT has been the backbone of global supply chain for years. A *supply chain* is a network of suppliers, distributors, and consumers; it also includes transportation between the supplier, the seller, and the final consumer. Thus, the environmental effects of researching, developing, manufacturing, storing, transporting, and using a product, as well as disposing of the product's waste, must also be considered part of the supply chain (Raghavendran *et al.*, 2012). The sustainable performance of supply chains is suggested by Allal-Chérif (2010) to be more challenging than ever for information technology (IT) departments due to the complexity and interdependency of ICT networks, yet ICT makes archiving ENP possible. For example, ICT can be used to identify ways in which to measure a product's pollutant substances or contribution to global warming in CO_2 equivalency terms. This carbon footprint can be analyzed and lowered by means of ICT-enabled tools that compare the company's ENP to current standards.

2.2 ICT-based procurement

The procurement function can play a significant role in improving organizations' ENP because of its ability to transform intraorganizational ICT networks into integrated management programs while using the Internet and interorganizational tools as platforms for managing supply chains and supplier relationships (Allal-Chérif, 2010). Ramkumar and Jenamani (2015) suggested that procurement is considered 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 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 the use of 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). 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). However, a review of previous work showed that EP systems have rarely been investigated in the context of GP. 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 green procurement (Raghavendran *et al.*, 2012).

Probably the first to examine the direct relationship between GP and EP were Walker and Brammer (2012), who 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. The authors concluded that (a) greater communication between buyers and suppliers facilitates sustainable procurement by enhancing information exchange and collaboration and, hence, the ability of buyers to implement sustainable procurement policies in their supply relationships, and (b) the greater use of EP capabilities facilitates sustainable procurement by offering new ways to operationalize sustainable procurement (Walker and Brammer, 2012). However, there is a lack of empirical studies that looks at the relationship between EP and GP, leaving only handful studies that reviewed that drivers and challenges of EP from sustainable procurement perspective. For example, Wahid (2012) investigated the factors that affect the implementation process of the EP infrastructure in the public sector from a green information system perspective, and determined that legal, technological, and managerial factors affected the implementation of the sustainable EP infrastructure. Another study by 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.

Generally, the literature reviewed suggests that the adoption of 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, many suggests further improvement to existing EP platforms is required (Adjei-Bamfo *et al.*, 2019; Raghavendran *et al.*, 2012; Wahid, 2012). Interestingly, a recent study put forward big data technology as the next improvement for sustainable EP. Talamo and Atta (2019) investigated 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; and suggested that the capabilities of BDA may represent a significant driver for improving the monitoring and control processes of sustainable service performance. This is an indication that this study is in harmony with recent academic studies' recommendations to attempt to combine some of big data's inherent capabilities with EP to improve organizations' ENP.

2.3 The impact of big data

Big data has made quite an impact in the past decade in areas such as hospitality, transportation, health, governance, and e-commerce (Akter and Wamba, 2016; Victor and Maria, 2018). Therefore, with the emergence of big data, improving ENP is becoming more realizable, as big data contributes to the realization of not only an information explosion but also a technological one, ensuring that the values generated from a massive amount of data can be collected, shared, and analyzed to facilitate better decision making in the procurement function.

2.3.1 Overview of the concept of big data

The term *big data* was used originally by NASA scientists to refer to the visualization challenge facing systems with a large amount of dataset that are ubiquitous in nature (Cox and Ellsworth, 1997). Currently, *big data* is a vast term referring to huge or complex datasets for which working with conventional data processing applications is insufficient (Wu *et al.*, 2016); 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 broke down the process of 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, as well as to 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 process of insight extraction from big data (Labrinidis and Jagadish, 2012).

BDA consists of the analytical techniques and tools necessary to obtain actionable insights from big data to improve business performance, deliver sustainable value, and deliver a competitive advantage (Fosso Wamba *et al.*, 2015). Anitha and Patil (2018) suggested that supply chain data analytics can be classified into three main types. The first type is *descriptive analytics*, which is used mainly to analyze what is happening now in order to answer the question of what happened in the past. Descriptive analysis identifies historical data and analyzes patterns (Anitha and Patil, 2018). It is also used to identify problems and opportunities in the field of SCM within existing processes and functions (Wang, G. *et al.*, 2016). The second type is *predictive analytics*, which uses quantitative and qualitative methods to analyze real-time and historical data to estimate the past and future levels of integration of business processes among functions or companies, as well as the associated costs and service levels. Predictive analytics is used to project what might happen in the future and why it might happen (Wang, G. *et al.*, 2016). The third type is *prescriptive analytics,* which anticipates why something has happened. It collects data continuously to re-predict events, enabling decision-makers to increase their prediction accuracy to make better decisions. Prescriptive analytics explains the reasons why certain events occurred. The aim when using prescriptive analytics is to improve business performance (Gruenen *et al.*, 2017).

Currently, contemporary firms and business sectors of all sizes are leveraging BDA resources and expertise to create marketplace advantages over peer firms that choose not to employ BDA or cannot employ it effectively. BDA has already had a great impact on various areas, such as e-commerce and SCM, helping in making short-term decisions with a limited number of actors in a competitive market environment (Chen, H. *et al.*, 2012; Kim, G. *et al.*, 2014). In fact, because of BDA's capability, its employment is no longer a nicety but a competitive necessity in dynamic markets (Baek and Park, 2015).

2.3.2 Big data in government operations

Although the business sector is leading in big data's development and application, the public sector has begun to derive insight to help support decision-making in real time from fast-growing, in-motion data from multiple sources, including the Internet, biological and industrial sensors, video, email, and social communications (Kim, G. *et al.*, 2014). For example, in 2012, the United States federal government announced a $200 million big data research and development initiative involving multiple federal departments and agencies to advance state-of-the-art core big data technologies; accelerate discovery in science and engineering; strengthen national security; transform teaching and learning; and expand the workforce needed to develop and use big data technologies (Office of Science and Technology Policy, 2012). In addition, the European Union Commission is teaming up with European industries, researchers, and academia in a big data public–private partnership to cooperate in data-related research and innovation, strengthen the data value chain, enhance community building around data, and pave the way for a thriving data-driven economy in Europe (European Commission, 2019). In fact, big data's application in governments has resulted in new opportunities and has the potential to transform e-government services and the interaction between governments, citizens, and the business sector (Lnenicka and Komarkova, 2019).

Many governments have widely implemented and used e-government systems. IT service and infrastructure has been reported as one of the major public procurements and investments in recent years (Choi *et al.*, 2018). The adaptation of big data–driven e-government systems was thought to be an effective tool for corruption reduction, showing the positive impact of e-governance using national-level data (Suresh *et al.*, 2013). Through the use of e-government systems, governments' transparency will increase and their plans and policies will be made clear to the public; thus, analyzing the problems and challenges in the growth of a nation can be done transparently (Dwivedi *et al.*, 2019). In addition, big data can assure not only the fast delivery of services but can also facilitate the analysis of the records of every task or action performed by a government, thus providing a clear calculation of the government's income and expenditures (Dwivedi *et al.*, 2019). Moreover, big data can help governments make the best decisions based on a fast data-processing system in areas such as defense, healthcare, research, and policy (Dwivedi *et al.*, 2019). Radu *et al.* (2018) suggested that when policymakers have the right technical and individual capabilities to use big data, they will be able to draft well-grounded strategies and policies. Finally, big data has made an impact on a number of urban domains, especially when their functionality involved the same core enabling technologies—namely, sensing devices, computing infrastructures, data-processing platforms, and wireless communication networks—for policy and strategy as they did for the creation of sustainable smart cities (Bibri, 2018a; Dameri, 2016).

Nevertheless, deploying big data in government operations has many challenges. Kim, G. *et al.* (2014) categorized these challenges as silo, security, and variety challenges. Government agencies typically have their own warehouse, or silo, of confidential or public information, and agencies are often reluctant to share what they might consider proprietary data. Thus, a significant challenge is faced when trying to integrate data from various government agencies and departments, as communication failure is often the result (Kim, G. *et al.*, 2014).

2.3.3 Influence of big data on procurement operations

Decision-making and procurement planning have emerged as fundamental and essential business processes that relate to the economic efficiency of an overall supply chain associated with service and product delivery (Choi *et al.*, 2018). In the past, analytical tools were based on historical data, meaning any decisions made were derived from out-of-date information (Hickey, 2018). In addition, the lack of knowledge about demand responses or behavioral aspects of decision making within procurement processes is a significant cost driver in modern supply chains (Bock and Isik, 2015). To improve this situation, systematic feedback must be provided to decision-makers to allow them to analyze business intelligence for procurement planning and inventory warning (Guo *et al.*, 2017). Accordingly, the demand has been significant for sophisticated decision support in the procurement and supply chain context based on data analytics (Hilletofth *et al.*, 2016). Nowadays, BDA is found to play an important role in this type of decision making, with prediction techniques using large data sources to evaluate what would have happened under different circumstances (Choi *et al.*, 2018). In fact, the age of BDA is equipping procurement functions with much more detailed information, often in real time, thus putting businesses in a better position to make smarter and more accurate decisions about spending, managing suppliers, and developing stronger procurement strategies (Hickey, 2018).

Big data 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). Therefore, BDA could help procurement operations make decisions in three key specific areas. The first area is risk management. BDA provides procurement functions with greater access to both 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 that it is 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 the adoption of a large amount of structured data with reporting and predictive purposes and from becoming predictive rather than reactive (Moretto *et al.*, 2017). Therefore, by configuring specific business rules, EP systems will be able to predict demand for certain stock within an organization and then ensure that the correct resources are sourced based on quality, price, and supply (Hickey, 2018).

Through big data, organizations can interpret past and current trends and make future predictions based on countless information sources, which is especially helpful in procurement and SCM (Moretto *et al.*, 2017). However, implementing big data in procurement does not come without challenges. The main challenge is related to acquiring data from diverse sources and storing them for value-generation purposes; the challenge then becomes managing and securing these data (Sivarajah *et al.*, 2017). Furthermore, while the potential benefits of big data are exponential for procurement decision making across the private sector, the public sector still faces steep practical, legal, and ethical barriers when seeking to exploit big, open data (Choi *et al.*, 2018). Nevertheless, it was suggested by Hickey (2018) that, to unlock big data's potential in procurement operations, training and choosing the most suitable EP system must play a key role in improving a business' procurement strategy. Once these two things are in place, procurement functions can begin to reap the benefits of big data.

2.3.4 Impact of big data on protecting the environment

Nowadays, it has been reported that large-scale datasets and analytics are increasingly being used by government agencies, NGOs, and private firms to forward environmental protections; they achieve this by reducing energy and resource consumption, greenhouse gas emissions, and long-lasting harmful effects on the environment, improving environmental performance (Wu *et al.*, 2016). For this reason, more academic studies are exploring the many green issues related to the concept of big data. Such studies have investigated a wide spectrum of green issues, such as the impact of big data on reducing carbon emissions (Louhghalam *et al.*, 2017; Zhao *et al.*, 2017), the advantage of using big data in green building technology (Fang, 2018; Lu *et al.*, 2018), the influence of big data on green advertising and pricing policies (Liu, P. and Yi, 2017), the opportunities for green human resource practices within big data (Singh and El-Kassar, 2019), and the role of big data in achieving a sustainable supply chain (Jiao *et al.*, 2018; Kaleel Ahmed *et al.*, 2018; Khan, 2019; Samvedi *et al.*, 2018). However, although there is a absence of research focusing on the impact of big data on GP and on GPP, there are recent studies suggesting that utilizing big data capabilities would improve EP platforms in the areas of commodity pricing and product cost, spending analysis, risk management, predictive analysis, compliance, quality and reliability, and collaboration (Hickey, 2018; John, 2016). Consequently, this would assist procurers in making better decisions regarding the selection of green products and services.

2.3.5 Current issues related to big data

Big data could be a powerful tool for addressing various problems by offering new insights into areas as diverse as health care, governance, security, and climate change. However, more data is not always better data. Big data, for some, is seen as a troubling manifestation of “Big Brother,” enabling invasions of privacy, decreased civil freedoms, and increased state and corporate control (Boyd and Crawford, 2012). Furthermore, the characteristics of data in the big data concept have liability implications, such as the question, “When data originate from long and complex value chains, who is responsible when inaccurate data or analysis leads to negative consequences?” Such concerns can be complicated by legal and regulatory restrictions on what data can be shared, such as in health care and e-government contexts (Thomas and Leiponen, 2016). In addition, the value-added of big data is still questionable because of the subjective nature of value of big data, and big-data-derived information users determine how to interpret and use those information (Brinch, 2018). Thus, BDA can be of limited value if the decision-maker and employees within the organization are unable to understand the analysis (Labrinidis and Jagadish, 2012). In fact, it has been argued that obtaining the data and conducting accurate data analysis are not the biggest obstacles in BDA but that the adoption barriers are mostly related to managerial and cultural resistance to change (LaValle *et al.*, 2011).

Furthermore, big data can sometimes lead to finding false correlations, also called *spurious correlations*. For example, if an employee analyzes the mobile phone data of a customer to check the amount of time the customer spends with another person, to identify the important people in the customer’s life, and finds that the customer spends more time with colleagues than family, it does not necessarily mean the customer's colleagues are more important than are the customer's family (Boyd and Crawford, 2012). The final challenge associated with BDA is the recruitment of fresh talent and the training of current employees in big-data-specific skills, as many universities still have not incorporated BDA into their management programs (Gupta and George, 2016).

2.4 Literature review summary

This overview of the literature demonstrates that big data can be used to predict production processes more accurately than can conventional EP platforms and to support efficient decision making, thus increasing ENP (Song, M. *et al.*, 2017; Talamo and Atta, 2019). With BDA capabilities, organizations are able to possess a huge and rich source of social, human behavioral, and environmental data; further, 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). Furthermore, organizations can employ big data in two forms: first, as evidence that they are complying with government regulations pertaining to their industry and sector, and second, to launch investigations to determine the cause of an environmental problem (Mason, 2018). In addition, 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 of the ENP enablers and improve their monitoring and control processes for ENP using the emerging capabilities of BDA (Dubey *et al.*, 2017; Talamo and Atta, 2019). Hence, the literature review findings demonstrate the gap of the literature and the importance of this study, and that employing big data can establish a framework for sustainability in the IT infrastructure, such as EP platforms, and in organizations, which could reduce their overall environmental impact and unlock new efficiencies to improve GP.

In this chapter, we aimed to pave the way for the next chapter, in which a conceptual model is developed to empirically test and evaluate propositions concerning the effects of some emerging big data capabilities on ENP under the influence of EP.

CHAPTER III. CONCEPTULIZATION

The purpose of this study is to examine how analyzing e-procurement (EP) can improve firms' environmental performance (ENP) against the background of big data. The literature review chapter concluded that in the age of big data, production processes can be more accurately predicted, thus improving EP performance and green decision-making while increasing environmental efficiency. Hence, to hypothesize, build, and test a conceptual framework, this study focuses on the inherent big data capabilities, including technological capabilities (TC), human capabilities (HC), and data-driven culture (DDC), and their impact on ENP.

To hypothesize and build a convincing conceptual model, this study follows Imenda (2014) recommendations for building conceptual frameworks in quantitative research by: (1) defining the research problem (this is highlighted in Chapter 1); (2) reviewing the available literature and identifying research gaps (Chapter 2); (3) identifying relevant theoretical structures; and (4) applying these theoretical structures to the research problem. Accordingly, the theoretical foundation for this study includes the resource-based view (Barney, 1991), the natural resource-based view (Hart, 1995), and the dynamic capability framework (Teece *et al.*, 1997). In this chapter, we introduce the reader to these theories and their development, which relate big data, EP, and ENP. Then, we demonstrate how these theories and frameworks can be used to develop related constructs to build the study's conceptual model.

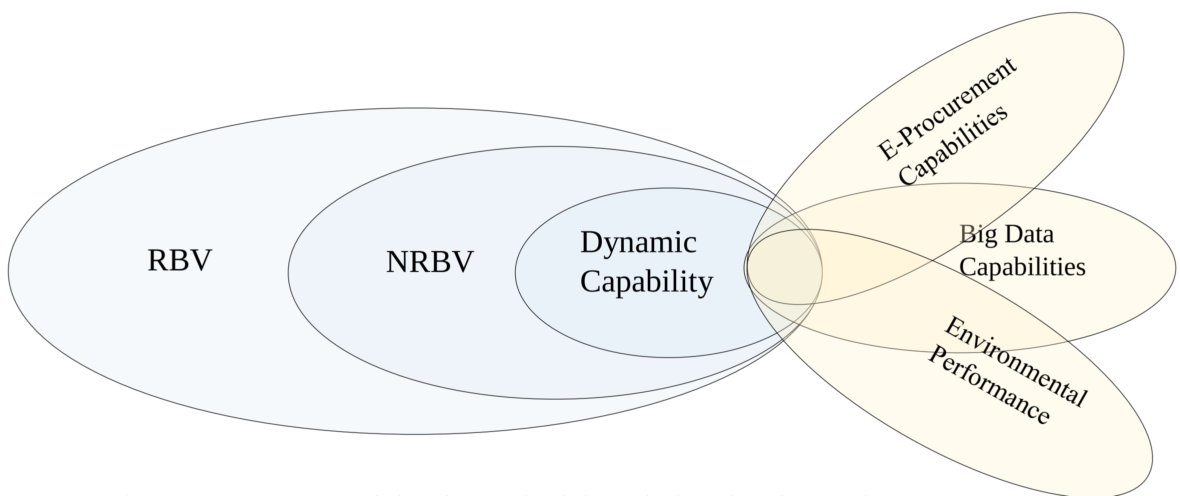


Figure 3. 1 Layout of the theoretical foundation for the study

3.1 Overview of theoretical foundation

The study's foundation is the dynamic capability framework (DC), first introduced to examine how and why certain firms have a competitive advantage in a complex and rapidly changing environment (Winter, 2003; Zahra *et al.*, 2006). It is thought to be an extension of the resource-based view (RBV) of a firm theory, which is an influential theoretical framework first introduced by Barney (1991) that identified how firms' achieve a competitive advantage and how that advantage might be sustained over time. DC is suitable for this study because big data require many complex and cutting-edge resources. The concept of DC is already helping businesses and operations to be more agile and dynamic.

3.1.1 Resource-based view of a firm theory

RBV theory focuses on firm-level determinants of organization performance relative to traditional industry-level variables, which is widely regarded as its key advantage (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 resource bundles that are heterogeneously distributed across firms, where 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 a sustainable competitive advantage (Barney, 1991). The VRIN framework states that resources should first be valuable and generate adequate value for the firm in some way, ranging from sales, to efficiency, to profits (Barney and Hesterly, 2010). Such resources, apart from generating value, should also be rare in nature and not easily available. If they were easily available, then they would not be relevant to generating a competitive advantage (Barney and Hesterly, 2010). Furthermore, these resources must not be easily imitable; ease of imitability would reduce the resources' worth, making it easy for other organizations to acquire them (Barney and Hesterly, 2010). Finally, these resources must be effectively organized to achieve a competitive advantage.

However, the RBV's growing influence has long provoked significant debate and critique in the academic community. For example, RBV explains competitive heterogeneity based on the premise that close competitors' resources and capabilities differ in important and durable ways, which in turn affects their competitive advantage. Under this premise, the RBV implies a static approach to competitive capabilities (Helfat and Peteraf, 2003). In addition, authors have questioned the RBV's failure to account for the biophysical environment, including the critical natural resource constraints that provide the context for a firm's creative ability. Kraaijenbrink *et al.* (2010) suggested that RBV critiques fall into eight categories: (1) the RBV has no managerial implications; (2) the RBV implies infinite regress; (3) the RBV's applicability is too limited; (4) sustained competitive advantage is not achievable; (5) the RBV is not a theory of the firm; (6) VRIN is neither necessary nor sufficient; (7) the value of a resource is too indeterminate to provide for useful theory; and (8) the definition of resource is unworkable. Despite these criticisms, Peng (2001) asserted that even the RBV's critics would accept that its paradigm represents an innovation in modern management science that paved the way to many extensions and further theory development.

3.1.2 Natural resource-based view

The natural resource-based view (NRBV) of a firm, first expounded by Hart (1995), incorporates the RBV, and proposes a natural resource-based view grounded in a firm's relationship with the natural environment. NRBV theory states that the RBV fails to take into account the biophysical environment and critical natural resource constraints that provide the context for capability building (Hart and Dowell, 2011). It further suggests that modern conceptualization has failed to recognize that natural processes, such as food protection, ecological services, and biological and cultural diversity sustain essential human society and social organization (Hart and Dowell, 2011). Thus, the NRBV incorporates three interrelated strategies: pollution prevention, product stewardship, and sustainable development within the RBV paradigm (Hart, 1995). The components of which are: (1) pollution prevention strategies reduce emissions using continuous improvement methods focused on well-defined environmental objectives; (2) product stewardship is realized by integrating life cycle assessment (LCA) in the product-development process; and (3) sustainable development strategies based on a strong sense of social-environmental purpose are implemented over an extended period to develop low-impact technologies (Hart, 1995). Thus, the NRBV theory advances propositions for each of these strategies and identifies their connection with achieving a sustained competitive advantage and improved firm performance (Hart and Dowell, 2011). This may be accomplished by initiating green practices that lead to a superior competitive advantage in terms of lower costs, reputation, legitimacy, future position, and long-term growth (Masoumik *et al.*, 2014).

In general, NRBV theory is well established in the literature; thus, several authors have developed and extended NRBV to offer additional insight into its potential capabilities. For examples, see also Ageron *et al.* (2013), Menguc and Ozanne (2005), and Shi, G. V. et al. (2012). However, both the RBV and NRBV have been criticized for their failure to acknowledge intangible resources, such as knowledge and learning, as key determinants of strategic advantage in rapidly changing environments (Sayeed and Gill, 2009). The DC framework overcomes these issues by suggesting that competitive advantage is influenced by unique dynamic processes that reconfigure resources, asset positions, and the evolution path adopted by the firm (Teece et al., 1997).

3.1.3 Dynamic capability framework

Teece et al. (1997) defined being “dynamic” as having the ability to renew competences to achieve congruence with the changing business environment, and “capabilities” as the key role of strategic management to appropriately adapt, integrate, and reconfigure internal and external organizational skills, resources, and functional competence to match the requirements of a changing environment. DC argues that firms’ competitive advantage lies with their managerial and organizational processes, shaped by their specific asset positions and the paths available to them (Teece et al., 1997). To further explain this, DC suggests that managerial and organizational processes have three roles: (1) coordination/integration (a static concept), where strategic advantage requires managers and processes to integrate external activities and technologies; (2) learning (a dynamic concept), where the learning process includes repetition and experimentation that facilitates better and quicker task performance, and identifies new production opportunities; and (3) reconfiguration (a transformational concept), which requires constant market and technology surveillance and a willingness to adopt best practices in a rapidly changing environment. Further, a firm's strategic posture is also determined by specific assets, including its difficult-to-trade knowledge assets and complementary assets, as well as its reputation and relational assets. These assets determine its competitive advantage at any given point (Teece et al., 1997). Finally, DC's notion of path dependencies recognizes that "history matters," suggesting that a firm's previous investments and its repertoire of routines constrain its future behavior and predict its opportunities (Teece et al., 1997).

DC's scope of action was expanded by Teece (2007), as shown in Figure 3.2, who defined them as the ability to (1) perceive opportunities (sensing), where competitive organizations continuously scan, search, and explore across technologies and markets, both 'local' and 'distant,' to identify and shape opportunities; (2) appropriately and effectively taking those opportunities (seizing), which involves maintaining and improving technological competences and complementary assets; then, when the opportunity is ripe, investing heavily in the particular technologies and designs most likely to achieve marketplace acceptance; and finally (3) accordingly reorganizing the firm's resource allocation (reconfiguring), which may include many important activities during enterprise growth, such as business model redesign, asset-realignment activities, and revamping routines (Teece, 2007). Currently, DC is considered an antecedent of resources that bring competitive advantage in a dynamic market because they play a critical role in adapting to, and even capitalizing on, a rapidly changing environment (Eisenhardt and Martin, 2000; Teece, 2007; Teece et al., 1997; Winter, 2003).

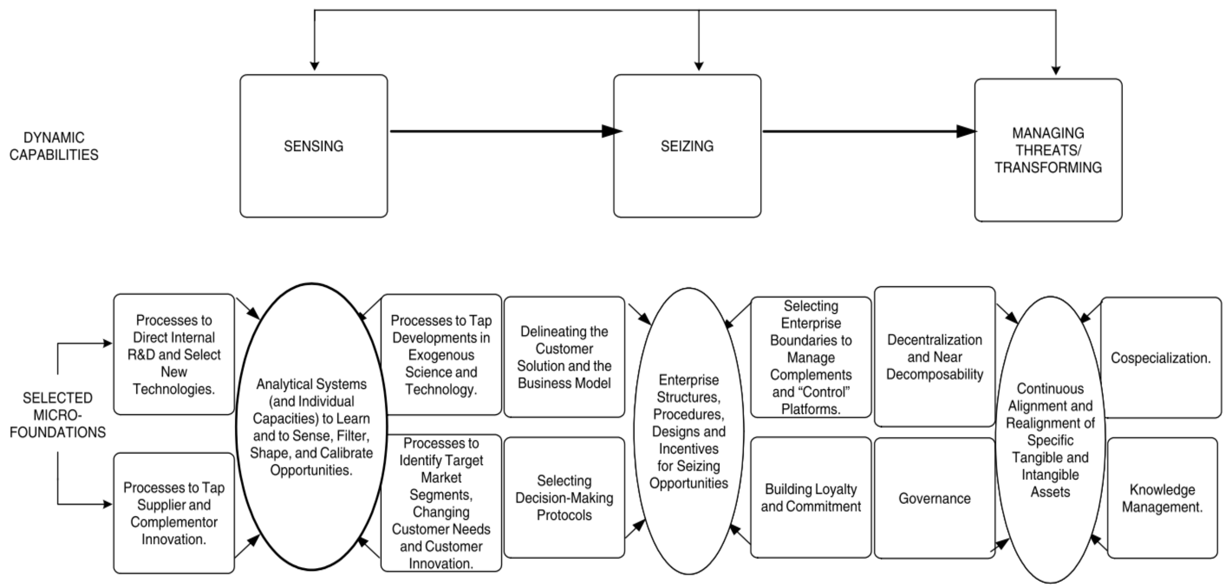


Figure 3. 2 Foundations of dynamic capabilities and business performance (Teece, 2007)

3.2 Theoretical overview of big data analytics capabilities

Akter et al. (2016) attempted to analyze the impact of BDA on firm performance from the RBV theory perspective, introducing a big data analytics (BDA) capability model (BDCA) to predict firm performance. They derived three key BDCA building blocks: organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (i.e., analytic skill or knowledge). However, in a growing body of knowledge, DC is more frequently used to conceptualize big data capabilities (Table 3-2). For example, Xu and Kim (2014) developed a modified dynamic capability framework to elaborate how organizations achieve dynamic capabilities using business intelligence and analytics (BI&A) via four sense and respond strategies: dynamic resource commitment, modular processes, learning processes, and context-specific governance mechanisms. These strategies involve (1) sensing, (2) responding, (3) leading, and (4) interpreting (Figure 3.3). Applying these sense and respond strategies can lead to improved organizational effectiveness and efficiency. Additionally, organizations monitor and interpret how their actions affect the market (Xu and Kim, 2014). Other researchers have suggested that achieving high performance via big data capabilities requires effectively deploying: (1) data, (2) technology, (3) people (technical skills and managerial skills), (4) organization (structural procedures, relational procedures, data-driven culture), and (5) procedural practice (Mikalef et al., 2019a). In fact, big data has unleashed many new capabilities: (1) data-driven culture, (2) data generation capability, (3) data integration and management capability, (4) advanced analytics capabilities; and (5) data visualization capabilities (Arunachalam et al., 2018).

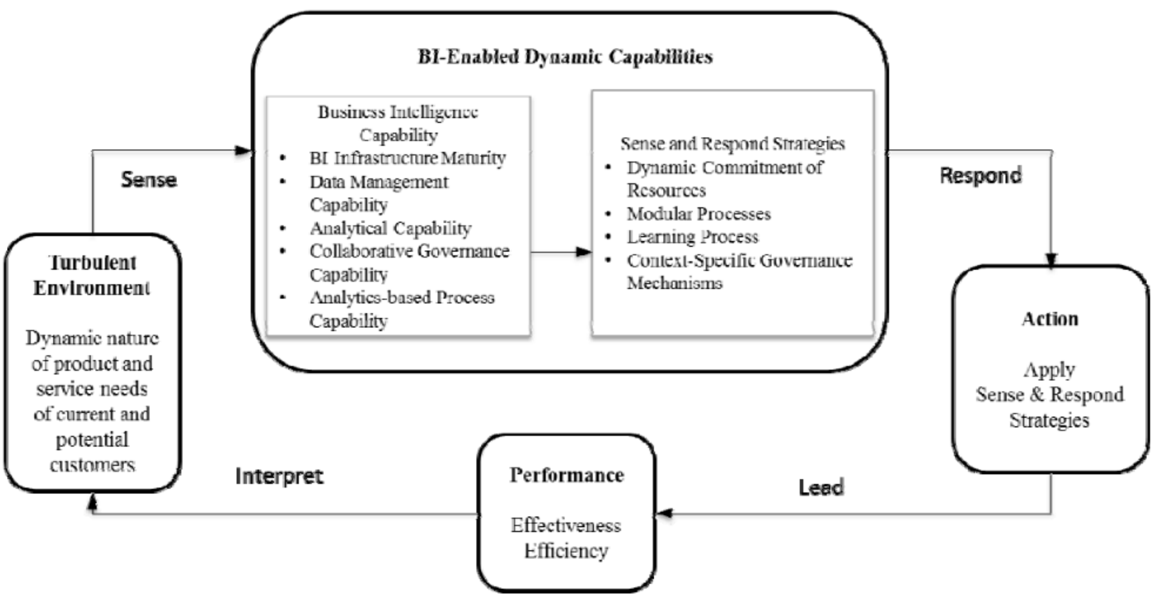


Figure 3. 3 BI-enabled dynamic capabilities as described by Xu and Kim (2014)

Table 3- 1 Summary of big data capabilities discussed in the previous literature

Big Data Capabilities	Source
(1) capability practices data collection and management (2) environmental data collection and management (3) analyzing environmental data and identifying discontinuities in the environment (4) identifying capability maladjustments (5) producing a request for change	Sidorova and Torres (2014)
BDA capability areas: (1) governance (the mechanism for managing the use of BI resources within an organization and aligning BI initiatives with organizational objectives) (2) culture (the assumptions, values, norms, and behavioral signs of an organization's members) (3) technology (developing and using hardware, software, and data within BI activities) (4) people (individuals within an organization who use BI as part of their job function) (5) processes (activities to gather, select, aggregate, analyze, and distribute information) (6) change management and capability (an organization's ability to meet the requirements of dynamic environments)	Olszak (2014)
(1) data-driven culture (2) data generation capability (3) data integration and management capability (4) advanced analytics capabilities (5) data visualization capabilities	Arunachalam et al. (2018)
(1) data (2) technology (3) people (technical skills and managerial skills) (4) organization (structural procedures, relational procedures, data-driven culture) (5) procedural practice should be effectively deployed	Mikalef et al. (2019a)

3.3 Procurement capabilities in theories

In the context of procurement, DC researchers have suggested that developing capabilities by executing strategic procurement plans helps firms improve their competitive advantages (McKelvie and Davidsson, 2009; Vaidyanathan and Devaraj, 2008). Procurement is a vital tool that reacts in dynamic business environments (Kim, M. *et al.*, 2015; Vaidyanathan and Devaraj, 2008). DC helps firms to sustain a competitive advantage in supplier relationships, which can improve the supply chain performance in a dynamic business world (Reuter et al., 2010). Daniel and Wilson (2003) identified eight distinct dynamic capabilities associated with e-business transformation. These capabilities fall into two groups: one associated with the need for innovation owing to e-business environment characteristics and the other encompassing the need to incorporate or integrate e-business into a business's existing operations. Hence, concept of DC plays a key role in confronting dynamic and changing business environments where firms need innovation and can integrate procurement functions into their existing operations (Daniel and Wilson, 2003).

In addition, by employing the NRBV theory, many researchers have investigated green procurement (GP) from two main dimensions: (1) product-based GP, which refers to obtaining and processing green materials or services based on a specific capability according to the firm's present strategic capabilities (Cristina De Stefano *et al.*, 2016; Lee, K.-H. and Min, 2015; Song, H. *et al.*, 2017b); and (2) process-based GP, which manages green supply processes by using the firm's ability to integrate, build, and reconfigure internal and external competences (Blome *et al.*, 2014; Lee, S.-Y., 2008; Song, H. *et al.*, 2017b). The researchers found that product-based GP capability was more effective than process-based GP, suggesting that product-based GP is more favorable for operational performance than process-based GP because process-based GP usually takes a long time to produce improvement (Song, H. *et al.*, 2017b). They also recommended future research applying the DC framework to measure a firm's detailed abilities and activities in responding to GP.

3.4 Formalizing the conceptual framework

3.4.1 The influence of technological capabilities on e-procurement

According to the RBV theory, resources can be tangible or intangible; tangible resources include buildings, IT infrastructure, connectivity, network, data sources, and capital (Barney (1991). Thus, from the RBV perspective, technological capability reflects firms' *"abilities to mobilize and deploy IT-based resources in combination or co-presence with other resources and capabilities"* (Bharadwaj, 2000, p. 171). In the early RBV research, many investigators examined technological resources and their impact on firm performance from the RBV lens. The earlier DC research also highlighted the importance of technological resources as an agile DC that must be effectively applied to achieve a competitive advantage in a dynamic environment (Eisenhardt and Martin, 2000; Teece et al., 1997; Winter, 2003). Technological capabilities (TC) are believed to enhance the relationships amid quality orientation and performance, and cost orientation and performance (Ortega, 2010).

In the big data era, firms require advanced TC that allows them to achieve a sustainable competitive advantage by combining rich data across the organization to deploy analytics that sense and respond to big data (Kitchens et al., 2018). In fact, the growing capability of BDA has facilitated the use of external data within organizations to achieve higher performance, where the resulting value to the organization is created through the (re)combination of internal and external big data (Thomas and Leiponen, 2016). Consequently, recent studies have focused on developing management teams' internal capabilities to utilize big data (Davenport and Harris, 2017; Thomas and Leiponen, 2016). Big data processing calls for high volume, high velocity, high variety, high veracity, and high value data, also known as the 5Vs of big data (Gandomi and Haider, 2015). Therefore, managing big data with the traditional IT infrastructure is not possible because of big data's 5V properties. Therefore, existing ICT systems require significant improvements to allow economic and efficient management. Big data adaptation requires a sophisticated tangible IT infrastructure, including cloud computing, big data systems, No-SQL databases, cognitive systems, deep learning, and other artificial intelligence techniques to integrate conventional ICT systems into a unified analytics system (Shi, Z. and Wang, 2018). In fact, interoperability of data infrastructure with other systems and applications must also be ensured before launching any big data project (Lnenicka and Komarkova, 2019). Dubey *et al.* (2019) classified big data tangible technological resources into three categories: (1) data connectivity, a technological resource that allows effective information sharing across different systems and applications; (2) novel technologies capable of handling volume, variety, veracity, and velocity to extract valuable and authentic information; and (3) basic resources, such as investing in big data and its related technology and tasks, to allow organizations to explore the standard operating procedures associated with implementing big data initiatives.

Conversely, Mikalef et al. (2019b) argued that tangible technological resources could not, by themselves, create BDA capabilities; the same applies to intangible technological resources, such as data availability. Currently, data, including texts, weblogs, graphs, audio, videos, GPS location information, sensor data, and other online data, are becoming more complex and diverse. Therefore, different tools and technologies are needed to handle and store data (Forsyth, 2012). The availability of data from various sources (internally and externally) has allowed large-scale adoption of data-driven decision-making capability (Karduck and Chitlur, 2016). In the big data environment, data is categorized as structured, unstructured, and semi-structured (Mohanty et al., 2013). However, the predictive analytics power of BDA, which deals mostly with structured data, was found to overshadow other forms of analytic techniques applied to unstructured data, which constitute 95% of big data (Gandomi and Haider, 2015).

In general, previous research suggested that BDA's value stemmed from maturity in tangible (ICT infrastructure) and intangible (data) technological resources (Gupta and George, 2016; Jeble *et al.*, 2018; Xu and Kim, 2014). Furthermore, because EP systems are embedded in and/or supported by ICT systems, the modularity at the system level helps modularity at the business process level (Xu and Kim, 2014). Thus, with big data TC (tangible and intangible), EP systems, data, and applications can merge to improve the modularity of the system and support new analytical demands. Therefore, TC (tangible and intangible) enhances decision-making in a big data environment, facilitating better EP performance. Therefore, the following hypothesis is proposed:

Hypothesis 1 *(H1).* The technological capabilities of big data have a positive relationship with e-procurement performance.

3.4.2 Human capabilities' influence on e-procurement

Drawing upon the RBV theory and recent work in big data, several human resources were found to be crucial in the big data environment. These resources are often categorized into tangible human skills, and intangible types (Gupta and George, 2016). According to RVB, a firm's human resources comprise its employees' knowledge, experience, problem-solving abilities, business acumen, relationships with others, and leadership qualities (Barney, 1991). Additionally, many studies have argued that technical and managerial skills are critical dimensions of human resources required for ICT capabilities to achieve firm performance (Chae et al., 2014; Mata et al., 1995), while others have stressed that some firm's low financial performance is related to employees' poor decision-making (Lee, H. et al., 2017; Raguseo and Vitari, 2018).

In the DC framework, learning is important to achieving higher performance and should be considered 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 hugely relevant to learning; their value depends on their employment, in particular, in organizational settings (Eisenhardt and Martin, 2000). Furthermore, in ICT projects, managerial and organizational dynamic processes include coordination/integration, learning, and reconfiguration. Coordination and integration refer to managerial or organizational routines that incorporate activities and technologies that are both internal and external to the firm (Sayeed and Gill, 2009). Moreover, big data's analytical capability was also found to facilitate learning by generating new business insights, thus helping organizations gain new opportunities (Xu and Kim, 2014). Additionally, recent studies have suggested that human capabilities (HC) required to work in a big data environment are based on two constructs pertaining to the respective skill types, technical and managerial (Jeble et al., 2018; Mikalef et al., 2019b; Wamba et al., 2017). These specific skill sets reflect the ability to handle big data's technological components and analytical requirements, and the ability to recognize big data's value and understand where to apply insight efforts. Similarly, this study proposes that specific big data technical and managerial skills are essential aspects of a firm's human resources capability.

Technical skills comprise the know-how required to use novel forms of technology to obtain intelligence from big data, and include competence in data extraction, machine learning, statistical analysis, data cleaning, and understanding programming paradigms, such as MapReduce (Gupta and George, 2016). In fact, technical system know-how was found to be valuable in data-driven decision-making (Vallurupalli and Bose, 2018). However, technical skills not only encompass the degree to which staff members have the appropriate skills to successfully accomplish their jobs, but also determine whether the staff's training and education background is suitable in relation to BDA requirements (Gupta and George, 2016; Sjusdal and Lunde, 2019). Thus, recent studies have recommended that firms should pay attention to their BDA management capability within the organization, because this will facilitate better utilizing BDA in operations, boosting process benefits and high value performance returns (Popovič et al., 2018). This involves developing a BDA strategy for the organization and implementing a plan to train, inform, and involve employees in BDA implementation (Popovič et al., 2018). Thus, having strong technical skills is required to convert data into actionable insight, because these skills lead to better decision-making (Mikalef et al., 2019a).

Conversely, Loon and Peing (2019) argued that many firms face big data adoption problems because they are unable to manage vast amounts of unstructured data, which is driven by a lack of expertise in the big data management field, and a lack of top management's support. This may explain why managerial skills have recently emerged as a core element. It is clear that top management should have excellent management skills, which are typically developed by individuals with a strong interpersonal bond with other individuals in the same organization and across different departments (Gupta and George, 2016)These managerial skills include developing a team with the appropriate skills and aligning team members' efforts with the firm's objectives (Mikalef et al., 2019a). In fact, Wamba et al. (2017) asserted that managers with the right skills could make the correct decision to improve the firms' performance through information extracted by team members. Under highly uncertain market conditions, the managerial bandwidth needed to solve business problems through analytics has emerged as a core contributor to high performance (Mikalef et al., 2019a). Managerial skills in the big data environment examine the degree to which manager (1) are knowledgeable about areas best applied to BDA; (2) understand the business needs of different functional areas and associated BDA opportunities; and (3) know how to evaluate the output extracted from big data. This was further justified by Mikalef and colleagues *"when the complexity of the environment increases, managerial insight may not be sufficient to process all relevant information and take decisions accordingly. A strong big data analytical capability allows firms to deal with this complexity and deliver insight, which can then be used by managers in order to sense, seize, and transform the way their firm operates"* (Mikalef *et al.* (2019b, p. 292).

Recall that RVB and DC both identified human skills as a primary capability required for smarter decision-making in a big data environment (Bibri, 2018b; Liu, H. *et al.*, 2019). Human skills were also found to be a crucial element in e-business transformations that involve (1) developing and critically evaluating business cases that incorporate substantial alterations to the business model using uncertain information, and (2) coordinating all stakeholders (Daniel and Wilson, 2003; Wang, Y., 2009). Hence, the merger of HC (technical and managerial skills) with the big data environment can improve analytical capability, thus leading to improved EP performance. Accordingly, HC (technical and managerial skills) enhance decision-making in a big data environment, leading to improved EP performance, forming the basis for the following hypothesis:

Hypothesis 2 *(H2).* Human capabilities related to big data have a positive relationship with e-procurement performance.

3.4.3 The moderating effect of data-driven culture

A key concept of big data is the ability to collect and analyze data to develop actionable insights and new knowledge leading to a competitive advantage and resultant higher performance (Ferraris et al., 2018). To continue improving supply chain effectiveness, firms will need to leverage large supply chain datasets in their ICT system (Yu et al., 2018). For example, firms could improve demand forecasting and supply planning by using their own data and supplementing with customer and supplier data, such as raw material data, delivery data, promotion data, and inventory data (Yu et al., 2018). Although modern organizations might have access to various reliable data sources, procurement professionals may find it difficult to locate and properly analyze them when required because they are submerged in a vast amount of data. Furthermore, procurement professionals are confused about how to select the best price for a product or service and decrease the unit price of purchased items to reduce the total cost of ownership for the best suppliers (Biazzin and Carvalho, 2019). Such confusion is created by the conflict between decisions based on their experience versus decisions based on the data, which may cause procurement functions to fall short and lead to incorrect decisions (Biazzin and Carvalho, 2019). This challenge increases when big data is applied in government operations, where it is essential for the public sector to guard individual privacy, data integrity, accountability, and transparency with stakeholders (Agbozo and Asamoah, 2019).

To leverage capabilities and gain the most from BDA's potential, BDA adoptions require radical changes to internal processes. Individuals and organizations may resist change because they often see change as a threat, a key barrier in BDA adaptation (Shukla and Mattar, 2019). This was explained by Aho (2015) assertion that transforming from traditional ICT such as EP to big data technology involves extensive change management and a new organizational culture to successfully transform the organization. To succeed in BDA, it is vital that employees at all levels are well informed about big data (Fosso Wamba et al., 2015). For this reason, Gupta and George (2016) emphasized that learning and data-driven culture (DDC) are two resources that firms should include to reap benefits from big data. Hence, DDC has emerged as an intangible resource, fundamental to other BDAC, and must be embedded into business routines related to BDA-driven decision-making (Arunachalam et al., 2018). DDC has three main characteristics (1) analytics should be treated as a valuable or strategic asset by an organization, (2) top management should support and leverage analytics across the organization, and (3) accessibility of data-driven insights are crucial to decision makers (Kiron and Shockley, 2011). Therefore, to gain the full benefits of big data, firms need to align existing organizational culture with big data capabilities across the organization (Fosso Wamba et al., 2015).

This study argues that vast and moving data generated by big data processes challenges procurement functions and decision-making. Thus, to achieve maximum increased performance from big data analytics, procurement functions also need to change the organization's decision-making culture (Frisk and Bannister, 2017). These changes will affect both human skills and technology. Hence, promoting a data-driven culture of technological capability and human capability can enhance decision-making in a big data environment to achieve improved EP performance. In line with this, the following hypotheses are proposed:

Hypothesis 3 *(H3).* A data-driven culture positively moderates the relationship between technological capabilities and e-procurement performance.

Hypothesis 4 *(H4).* A data-driven culture positively moderates the relationship between human capabilities and e-procurement performance.

3.4.4 The mediation impact of e-procurement on environmental performance

The relationship between ENP and operational performance is a major theme in the debate over the greening of organizations and the transition to sustainable development (Jabbour et al., 2015). Zhu and Sarkis (2004) suggested that ENP concerns managers for reasons ranging from regulatory and contractual compliance to public perception and competitive advantage, because environmental performance is used to measure a business's environmental protection and environmental management policy outcomes. Several authors (Chuang and Huang, 2018; Porter and Van der Linde, 1995; Pujari et al., 2003) affirmed in their environmental management studies that a higher ENP may also create good organizational performance and facilitate a competitive advantage. These authors explained this relationship using RBV, NRBV, and DC theories. From the NRBV perspective, firms are restrained by the natural environment, and proactive prevention can deliver improved ENP over ex post facto control (Hart, 1995). Judge and Elenkov (2005), applying the DC framework, argued that the pursuit of goals toward ENP requires the ability to adapt and innovate. Thus, by achieving higher ENP, firms can create greater competitiveness in the market. In other words, firms that are frontrunners in environmental protection have greater market competitiveness, meaning that they can charge higher prices for products, enhance their corporate image, and even sell their green technologies and services. Firms can develop new markets and gain a competitive advantage as a result (Chuang and Huang, 2018).

Similarly, to explain the relationship between EP and ENP, this study will apply RBV, NRBV, and DC theories. RBV and NRBV hold that specific sources potentially create a sustained competitive advantage. RBV emphasizes the significance of internal organizational resources, as opposed to external industry forces, for attaining strategic goals. To attain continued competitive performance, firms must accumulate resources that generate financial value (Barney, 1991). In addition, the NRBV argues that it is a firm's resource bundle rather than product deployment of those resources, that determines its competitive position (Hart, 1995). EP is defined as the use of Internet-based (integrated) ICTs to carry out all or individual stages of the procurement process, including searching, sourcing, negotiating, ordering, receiving, and post-purchase reviewing (Panayiotou et al., 2004). Hence, an EP system can be viewed as a firm's ICT-enabled resource. However, Vinekar and Teng (2012) suggested that ICT-enabled resources are pervasive, not rare; as such, competitors can also adopt or develop ICT-enabled resources. Yet, the RBV asserts that physical resources (e.g., ICT and EP systems) can provide a competitive advantage only if they surpass competitors' equivalent assets (Barney, 1991). In fact, Teo et al. (2017) suggested that firms can use ICT-enabled resources to develop green technologies capability, integrate them with interfirm technologies, and develop and deploy processes to harness them. In other words, firms can use ICT-enabled resource 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 sustainability practices (a resource or capability) are enhanced by appropriate ICT resources and practices. Co-specialization requires two resources to exist simultaneously to be of value to the firm (Clemons and Row, 1991; Sayeed and Onetti, 2018). For this reason Nevo and Wade (2010) viewed ICT-enabled resources as having a superior strategic capability than other organization resources in isolation.

The previous literature shows that many studies approached the impact of EP implementation on ENP from different perspectives, yet they all concluded that EP plays a role in improving organizations' ENP. In addition, in applying the RBV, NRBV, and DC, we suggest that a positive relationship exists between organizations' EP performance and their ENP. Pursuant to this, the following hypothesis is proposed:

Hypothesis 5 *(H5).* E-procurement performance has a positive influence on organizations' environmental performance.

Previously, we argued that, according to the RBV and DC framework, big data capabilities may stimulate EP operations, consequently increasing firm performance. Consistent with this, our study also proposes that big data capabilities can improve a firms' ENP, but the effect is indirect and is mediated by EP performance. We argue that big data capabilities lead to better and greener decision-making, which in turn enhances ENP. Additionally, Chen, Y. S. and Lin (2015) suggested that green dynamic capabilities developed via green human capital to create and sustain a competitive advantage via resource application and knowledge. Hao et al. (2018) also highlighted that high-level managerial skills are essential for developing paths and practices that internally sustain entrepreneurship, and that high-level technical skills are essential for externally integrating new emerging technologies and sustainable characteristics.

The above arguments imply a potential mediating role for EP. The key to actualizing this potential EP lies in more quickly managing and exploiting the sustainable market and green policies via big data to build a greener EP system that ultimately enhances its ENP. Therefore, big data capabilities (TC and HC) drive ENP through the EP system. Consequently, the following hypotheses are proposed:

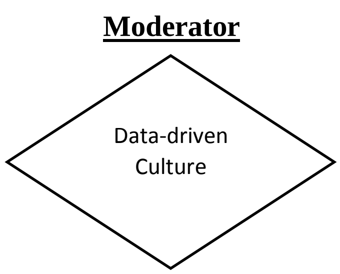
Hypothesis 6 *(H6).* Technological capabilities under the mediation effect of e-procurement performance have an influence on environmental performance.

Hypothesis 7 *(H7).* Human capabilities under the mediation effect of e-procurement performance have an influence on environmental performance.

3.5 Chapter summary

In this chapter, we provided an overview of the theoretical background used to develop hypotheses and build a conceptual framework that can be tested to answer the research questions. The chapter examined the internal big data capabilities of TC, HC, and DDC's impact on EP and consequently on firms' ENP from the perspective of the RVB, NRBV, and DC theories. Hence, this study developed the following arguments:

- Big data's (tangible and intangible) technological capabilities enhance decision-making in a big data environment to improve EP performance.
- Human capabilities related to big data (technical and managerial skills) enhance decision-making in a big data environment to improve EP performance.
- Promoting a data-driven culture that combines technological capabilities and human capabilities can enhance decision-making in a big data environment to improve EP performance.
- A positive relationship exists between organizations' EP performance and their ENP in a big data environment.
- Big data capabilities (both technological and human) can drive ENP through the EP system.



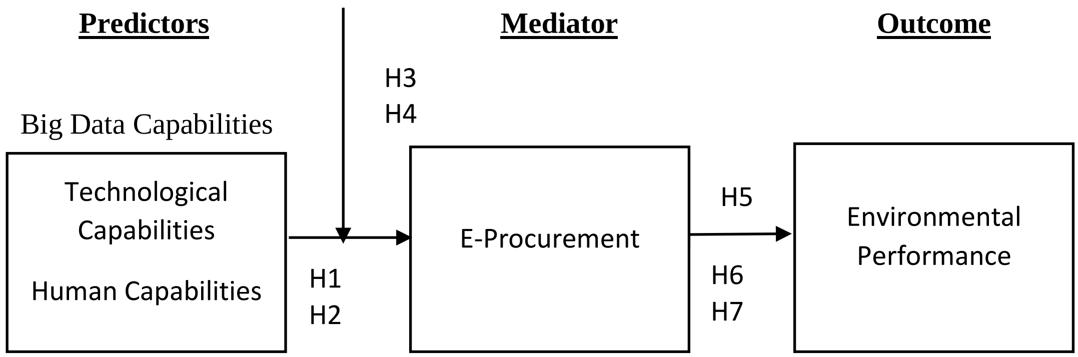


Figure 3. 4. Conceptual framework

The conceptual framework (Figure 3.4) illustrates a detailed model of the hypothesized relationships as presented in this chapter and the study's seven following hypotheses. The next chapter discusses research methods for measuring and testing the relationships presented in Figure 3.4.

CHAPTER IV. RESEARCH METHODOLOGY

This chapter discusses methodological issues appropriate for empirically answering the research questions in hand and testing the hypotheses developed in Chapter 3. This chapter explains the study design, study setting and population. The constructs and exemplars of items used to measure constructs of environmental performance (ENP), e-procurement (EP), technological capabilities (TC), human capabilities (HC), data-driven culture (DDC) are presented. Further, this chapter presents the sampling technique used, data collection procedure, and the study rigor. Finally, the chapter closes with a description of ethical considerations and a summary of the study.

4.1 Research design

The formulation and adoption of an appropriate research method is a crucial element within a dissertation and must be addressed with great care (Marshall and Rossman, 2014). Because social research is an extremely complex process and is characterized by the availability of numerous research epistemologies, approaches, tools, and techniques, the adoption of an inappropriate research method can result in incorrect, inadequate, and even misleading outcomes (Marshall and Rossman, 2014). Social research theory and practice have been strongly influenced by two epistemologies, namely, positivism (quantitative) and interpretivism (qualitative; (Nachmias and Nachmias, 2008). The positivist epistemology, which is associated with deductive logic and quantitative tools and techniques, is based upon the principles of scientific research and is essentially objective and rational in its approach and execution (Nachmias and Nachmias, 2008). The interpretivist approach, on the other hand, is exploratory in nature and is associated with inductive logic and qualitative tools and techniques (Teddlie and Tashakkori, 2009). It is essentially probing in its outlook and makes use of a range of tools and techniques, including thematic analysis, content analysis, case study analysis, narratives, and subjective matter (Teddlie and Tashakkori, 2009).

A constructive positivism quantitative approach is opted to investigate whether some big data capabilities (TC, HC, DDC) can influence ENP under the mediation effect of EP. This approach is believed to offer a more clinical outcome to the research and builds on the recommendations of Lakshman *et al.* (2000), who argued that this approach offers a more detailed research output. The quantitative approach is based on the assumption that meaningful social research should be based on the physical observation of research-associated phenomena and helps to facilitate examination of the strength of association between quantified constructs (Howell, 2012). This is followed by the careful detailing of such observations and their subsequent analysis and validation with the help of acknowledged and established methods for the selection of samples, analysis of data, and validation of findings, thus providing a more scientific response to the research that helps to withstand the academic peer reviews (Saunder *et al.*, 2009).

The variables of interest for the study was gathered in a numerical format using the validated survey instruments. This study intends to assess the presence and impact of the relationship between the independent variables, the mediated variable and the dependent variable. The study involved the use of a survey instrument to facilitate the data collection process. This approach therefore provided a measurement that was analyzed as part of a more streamlined research thesis. It is accepted that this selection does not offer the human aspect of the research in relation to the issues on hand. This is accepted, but the research objectives imply that this section will provide a necessary measurement that can then be critically discussed more effectively.

4.2 Definition and variables/instruments

The data collection vehicle was via a survey questionnaire provided to a targeted sample group. The method has worked via the advice of Dörnyei and Taguchi (2009), who offered advice on developing questionnaires to better support research. Chapter 3 provided the basis for the survey design and constructs used in the study. Its noteworthy to addressed here that constructs do not correspond to reality; they are merely useful fictions that researchers attribute to phenomena. Therefore, scales do not reflect the true nature of a trait; they merely enable researchers to obtain interesting or useful insights about phenomena (Messick, 1993). Nevertheless, existing measures are used to suit the purposes of this study utilizing a survey instrument comprised principally of a 5-point Likert scale to measure the degree in which they agree or disagree with the information at hand. Those constructs and measures are presented in Table 4-1 and will be discussed in further detail in the following paragraphs.

4.2.1 E-procurement

EP is defined as the use of Internet-based (integrated) information and communication technologies (ICTs) to carry out individual or all stages of the procurement process including search, sourcing, negotiation, ordering, receipt, and post-purchase review (Panayiotou *et al.*, 2004). To measure EP performance in an organization, this study adopted "the perceived e-procurement quality" scale which was developed by Brandon-Jones (2006) in which the author attempt to measure the user-perceived EP through the dimensions of professionalism, processing, training, specification, content, and usability. The scale has been validated in further studies concerning contract compliance and procurement performance and found to be reliable with Cronbach alpha greater than 0.850; for example, see (Brandon-Jones, 2017; Brandon-Jones and Carey, 2011; Brandon-Jones and Kauppi, 2018; Sharabati *et al.*, 2015). However, we chosen to adopt only three dimensions for this study (processing, content, and usability) as they are more in line with this research objectives; thus, the scale shall consist of 9 items.

4.2.2 Environmental performance

ENP includes many indicators such as; controlling harmful waste such as carbon monoxide emissions, wastewater, or solid waste. However, to measure the improvement in ENP under the influence of EP and big data capabilities, this study used the "Environmental Performance Improvement" 6-item scale developed and adopted by Large and Thomsen (2011). This scale was found useful and reliable (Cronbach alpha of 0.950) in measuring the impact of some of the green supply chain capabilities (green supplier assessment, environmental commitment, green collaboration with suppliers, and strategic level of purchasing) on improving ENP (Large and Thomsen, 2011). In addition, this scale was also found used and adopted in the literature in investigating the relationship between green procurement and firms performance; for example see (Chithambaranathan *et al.*, 2015; Khaksar *et al.*, 2016; Laosirihongthong *et al.*, 2013; Van den Berg *et al.*, 2013; Zailani *et al.*, 2012).

4.2.3 Technological capability

TC within big data is suggested to be based on tangible and intangible resources. Tangible resources include IT infrastructure, buildings, connectivity, network, and a data source (Barney, 1991; Mikalef *et al.*, 2019b). Whereas, intangible resources is the availability of vast data from various sources (Mikalef *et al.*, 2019b). Therefore, to measure technological capability under big data concept, the study is used the 8-item scale recently developed by Mikalef *et al.* (2019a). This scale consists of three items to describe the intangible resources (data) in the organizations and five items that address the tangible technological resources (technological infrastructure). The authors also checked the construct validity, and it was determined that it is above the lower threshold of Cronbach alpha of 0.70.

4.2.4 Human capabilities

HC required to work in a big data environment were suggested to be based on two constructs pertaining to the respective type of skills: technical and managerial skills. Whereas technical skills reflects the level to which staff members have the appropriate skills to achieve their tasks successfully under the background of BDA (Gupta and George, 2016; Mikalef *et al.*, 2019a). Meanwhile, managerial skills examine the degree to which managers are knowledgeable about areas to apply to BDA, and understand the business needs of different functional areas and the opportunities BDA (Chen, Y. S. and Lin, 2015). Hence, to measure human capabilities in BDA (managerial skills and technical skills), We used the 2-dimension scale developed by Jeble *et al.* (2018). This 11-item scale was verified and validated by socio composite reliability (SCR), which was found greater than 0.7. Although this scale is relatively new, it had been adopted by Sivarajah *et al.* (2019) while investigating the role of big data on ERP system performance and by Sjusdal and Lunde (2019) in studying the role of organizational culture in BDA utilization. In addition, Jeble *et al.* (2018) findings have generated an increasing impact in the field of BDA in the recent literature (Côrte-Real *et al.*, 2019; Loon and Peing, 2019).

4.2.5 Data-driven culture

DDC is defined by three main characteristics: (a) analytics should be treated as a valuable or strategic asset by an organization, (b) top management should support and leverage analytics across the organization, and (c) the accessibility of data-driven insights are crucial to decision makers (Kiron and Shockley, 2011). Therefore, this study also adopted the 3-item scale developed by Jeble *et al.* (2018). As mentioned previously, this scale was validated by socio composite reliability (SCR), which was found greater than 0.7. Although it is newly developed sacle; however, it is increasingly used in the area of BDA as mentioned previously.

Table 4- 1 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)	ENP1. We have achieved a reduction of pollution and waste. ENP2. We have improved compliance with our organization environmental policy. ENP3. We have increased the level of recycling. ENP4. We have preserved the environment. ENP5. We have improved the environmental reputation of our organization. ENP6. We have improved the overall environmental performance of

		our organization.
Human Capabilities (HC)	Jeble *et al.* (2018)	HC1. Our procurement managers understand sustainable business development requirements of other managers, customers, and suppliers HC2. Our procurement managers are capable of coordinating related big data and predictive analytics activities in ways to assist other managers, customers, and suppliers HC3. Our procurement managers are capable of working with other managers, customers, and suppliers to define opportunities that big data could bring to our organization HC4. Our procurement managers can anticipate the future business needs of the other functional managers, suppliers and customers using big data HC5. Our procurement managers have good idea of where and how to use big data HC6. Our procurement managers are capable of understanding and evaluating the output produced from big data HC7. We offer training related to big data to our procurement staff HC8. We hire new procurement staff that already have big data and predictive analytics skills HC9. Our procurement staff has right skills on big data analysis to accomplish their jobs successfully HC10. procurement staff has suitable education on big data analysis to fulfill their jobs HC11. Our procurement staff is well trained on big data analysis
Technological Capabilities (TC)	Mikalef *et al.* (2019a)	TC1. We have gain access to huge, fast-moving, and unstructured data for procurement analysis TC2. We incorporate data from various sources into a data warehouse for easy access in the e-procurement platform TC3. We incorporate external data with internal e-procurement platform to enable analysis of procurement data TC4. We have explored or implemented parallel computing methods to big data processing TC5. We have explored or implemented various data visualization instruments in our e-procurement platform TC6. We have explored or implemented new types of databases in our e-procurement platform TC7. We have explored or implemented cloud-based services for data processing and performing analytics in our e-procurement platform TC8. We have explored or implemented open-source e-procurement platform to be used 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 make our procurement decisions based on data rather than intuition DD3. We are prepared to reverse our own intuition when data disagree with our viewpoint on procurement decisions

4.3 Study setting

This study is set to be conducted in the UAE. As mentioned in chapter 1, the government of the UAE has consistently endeavored to enhance the sustainability of its economy and promote a green economy by focusing on GPP in collaboration with relevant agencies to tackle climate-change issues in a way that is both economically logical and protective of natural resources. In addition, the UAE government always aims to be ahead of other governments in achieving high efficiency and excellence in public services. The UAE's economic diversification vison entails the use of some of the latest technologies and innovations as it aims to be at the forefront of global competitiveness (Zaatari, 2019). Recently, the UAE has shifted to artificial intelligence-enabled services, which necessitated the establishment of the Ministry of Artificial Intelligence (Halaweh, 2018). In addition, the Centre for the Fourth Industrial Revolution UAE, C4IR UAE, has launched a new initiatives jointly with the World Economic Forum to employ Artificial Intelligence (AI) tools in government operations that aims to enable governments and companies to make their procurement processes more efficient and transparent by employing a multi-stakeholder approach (Emirates News Agency, 2019).

Furthermore, in line with the UAE Cabinet Resolution No. 32 of 2014 on Federal Government Procurement Regulation and Storehouses Management, the UAE Ministry of Finance (MoF) developed an Oracle system for EP (UAE Minstry of Finance, 2019). The system aims to increase efficiency and speed up the work process in the (MoF) or other ministries and federal entities (UAE Government Portal, 2019b). However, each local government is using its developed EP systems, such as Abu Dhabi Government ePortal in Abu Dhabi, eSupply Portal in Dubai, and Sharjah Government ePortal in Sharjah (UAE Government Portal, 2019b). Therefore, it is safe to assume that almost all the UAE government entities are practicing sustainable EP operations and already started to implement business intelligence in their procurement practices.

4.4 Population

Before the large-scale data collection process began, attention and efforts were focused on understanding the population and respondents for this study. According to the UAE Government Portal (2019a), there are a little over 240 government entities in the UAE, among which 86 government (federal and local) entities are located in Abu Dhabi. The total workforce working in the UAE defense and public sector is 13% of the total UAE workforce, which comes to 838,136 people (UAE Government Portal, 2019c). Thus, this study aimed to target procurement professionals in the UAE government entities located in Abu Dhabi. Selecting Abu Dhabi was the most appropriate because it combines many local government and federal entities.

However, it is challenging to determine the total number of government employees working in Abu Dhabi. To further narrow the population to an acceptable target sample, it was determined that the respondents for this study must be employees with enough knowledge about the phenomenon under study, i.e., Big Data practices and EP in government organizations. Therefore, it was vital for this study to target government organizations located in Abu Dhabi who have already adopted business intelligence practices in their procurement function or considering adopting business intelligence. Thus, the key informant approach was followed in determining the population for sampling and data collection as suggested by Phillips and Bagozzi (1986). Using word of mouth, we have located and talked to six procurement experts working in Abu Dhabi public sector voluntarily. Moreover, based on these talks, we learned that a minimum of 23 government entities located in Abu Dhabi have already moved or planning to move to Business intelligence-based ep operation in the next two years. An initiative was also supported in our literature findings (Consultancy.org, 2019; Emirates News Agency, 2019).

Given the difficulties of locating and gaining access to enough key informants in each 23 government entities; hence, with the guidance of the informants, we have sent email invitations to these organizations with the statement of the purpose of the study. Only twelve entities have responded to this email and directed us to a point of contact (POC) in their entities. After contacting each of these POCs, we learned that the total employees working in procurement within their organizations were 580 employees which shall be the target for this study.

4.5 Survey design

The purpose of this study was to investigate the relationships between HC, TC, and DDC on ENP under the mediation influence of EP. The method of data collection for this research was a survey of the sample group. The method has worked in the past, per Dörnyei and Taguchi (2009), who offered advice on developing surveys to better support research. I used a six-part survey. Where, part one comprised the provisional demographic data conveyed the general information for group trends and for defining the sample group: age, professional status, and social aspects. The remaining five parts were cross-sectional survey research questionnaires designed to assess the respondents' perspective in the questions presented in Table 4-1 using a 5-point Likert-type scale, ranging from 5 (*strongly agree*) to 1 (*strongly disagree*). The survey was conducted using SurveyMonkey® to administer the qualitative instrument for its ease of use and ability to transform the collected data directly to SPSS.

4.6 Data collection procedure

4.6.1 Pilot study

Prior to start collecting data for the main study, a pilot study was performed to demonstrate the feasibility of the techniques used to administer the quantitative instrument (Bryman, 2016). Conducting pilot studies is considered an important phase in the preparation of proposals for hypothesis-testing studies. Glitches in the research design are often found and corrected during pilot testing, leading to a better-designed main study (Kraemer *et al.*, 2006). However, every correction casts doubt on whether any effect size estimate derived from a pilot study represents the true effect size in the main study (Kraemer *et al.*, 2006). Therefore, special attention was required to come up with a proper sample size for the pilot study. Connelly (2008) suggested that a pilot study sample should be 10% of a main study sample. However, Hertzog (2008), was cautious about this and asserted that it is not that simple, because in some cases, studies are influenced by many factors. Nevertheless, Isaac and Michael (1995) and Hill (1998) suggested 10 – 30 participants as minimum for pilots in survey research. Therefore, this study adopted both recommendations and suggested 30 to 58 participants for the pilot study, as the main study sample size is expected to be a maximum of 580 participants.

Based on the limited numbers of public entities that has agreed to participate in this study (12 entities), a pilot study was performed on one government entity that have a total of (63) employees working in procurement operations before going further with the main study. After coordinating with the POC and obtaining the approvals, I was provided with the emails of their (63) employees to contact directly with the survey attaching my email address to allow them to contact me if they have a question or have feedback on the survey. The pilot study was conducted using SurveyMonkey® to administer the qualitative instrument. Out of 63 potential participants, only 47 have completed the survey which was found acceptable as it was within the recommended pilot study size.

In order to check the reliability of the construct, I used Principle Component Analysis (PCA) as recommended by Samuels (2015) as a better verification method than Cronbach's alpha (α) for conducting a pilot studies . According to Samuels (2015), if PCA results on factor loading was above 0.7, then the results are acceptable. One the other hand, if any component loading results below 0.4, then this factor shall be removed from the scale and re-run the analysis. The PCA results (Table 4-2) shows that the reliability scores for each of the scales used in this study are above 0.07, hence they are acceptable.

Table 4- 2 Component matrix

Construct	**Component 1**
E-Procurement (EP)	.714
Environmental Performance (ENP)	.878
Human Capabilities (HC)	.941
Technological Capabilities (TC)	.892
Data-driven Culture (DDC)	.731

* Extraction Method: Principal Component Analysis (SPSS)

a. 1 components extracted.

Further, we tested the strength of the relationships between all constructs using bivariate correlation analysis (Pearson's *r*). Coefficient values between 0.10 and 0.30 are considered small or weak; those between 0.40 and 0.60 are considered moderate; and those over 0.70 are considered strong. The correlations between the variables are presented in the correlation matrix in Table 4-3. The data shows that there is an existing relationship between the constructs that varies between moderate to strong. However, there is a weak the relationship between EP and DDC.

Table 4- 3 Pilot Study Correlation Test Between the Constructs

Construct	A (EP)	B (ENP)	C (HC)	D (TC)	E (DDC)
A (EP)	1				
B (ENP)	.580**	1			
C (HC)	.643**	.756**	1		
D (TC)	.489**	.737**	.860**	1	
E (DDC)	.318*	.560**	.630**	.574**	1

Note. EP = e-procurement; ENP= environmental performance; HC = human capabilities; TC = technological capabilities; DDC= data-driven culture.

The results of the pilot study are considered promising and hence, we can move forward with the main study. However, there were some issues risen from the surveys there are required to be addressed prior to going further with main data collection. The pilot study survey was done in English language and some of the participants emailed me asking about meaning of some words and concepts. Although, there were enough definition on the concept used in this study, it seemed that due to the technical and academic language used in the survey, some participants did not grasp some meanings. Therefore, the survey was simplified and introduced and option for Arabic translated version of the survey for the main study survey. Moreover, in the question *"Are you working, or have you ever worked in procurement?",* few respondents answer was *"No"*. This indicate that some of the respondents were random and were not part of the target sample. Therefore, to avoid this in the main study, I introduced a screening question at the beginning of the main study SurveyMonkey® survey to ensure that only the respondents with the required characteristics take the survey and all other potential respondents would be disqualified. This screen question was *"This Survey requires some experience in procurement and technology. Before moving forward, please let us know if you have such experience".* If the participant answered *"No"*, this would take him/her to survey exist page, and If the answer is *"Yes"*, they shall continue with the survey.

4.6.2 Power analysis

Power analysis was conducted to determine the minimum required sample size of the main study. The Statistical power is the ability to find a difference when a real difference exists. It is the probability that null hypothesis will be rejected when it is false (Cohen, 1988). The sample size was based on power analysis for a logistic regression conducted using G*Power 3.1.9.4, software tool developed by Faul *et al.* (2009) and the procedures established by Lipsey and Aiken (1990). G*Power is used because of its ability to conduct a priori power analysis and compute effect sizes and to display graphically the results of power analyses. According to Cohen (1988), the effect sizes can be interpreted as small (effect size of 0.02), medium (effect size of 0.15), and large (effect size of 0.35). Therefore, we conducted an priori test using the number of predictors as four including the interaction effect as shown in the research model (EP, TC, HC, and DDC), with a medium effect size level (0.15), a moderate significance level (0.05), and a high power requirement of .95. The results show that the minimum required sample size amounts to 129 as shown in Fig. 4.2.

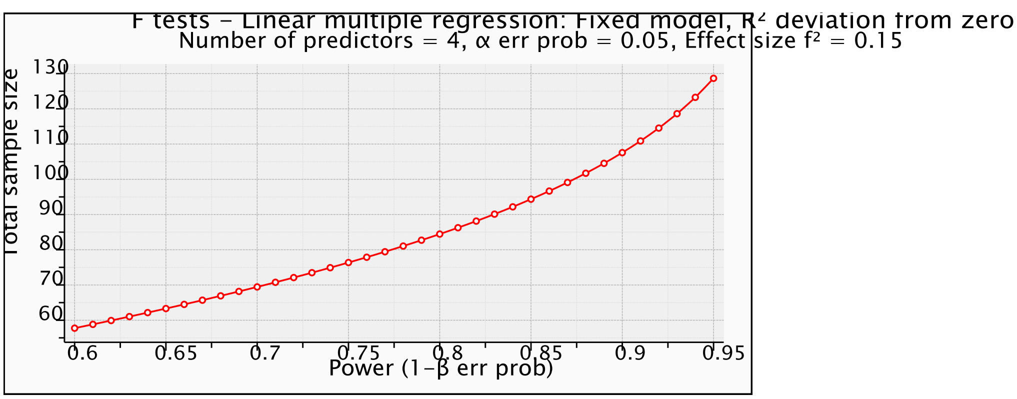


Figure 4. 1 Results of Priori test to determine minimum sample size from G*Power

4.6.3 Main study data collection

In June 2020, after permission was obtained from each employee's organization, a survey was sent via survey administration software platform SurveyMonkey® to 580 procurement professionals working in public organizations located in Abu Dhabi. A total of 286 respondents completed the survey, producing a response rate of 49.3%. To ensure that irrelevant results would not be recorded, we checked if their anomalies in the response and we found that there were 23 results came from the private sector, which it was eliminated. In addition, a question that checked whether respondents were working in a procurement function in their organization was used to eliminate 47 responses, leaving a final sample of 216 which above the minimum sample required according to the power analysis results. Table 4-4 presents the demographic characteristics of the sample.

Table 4- 4 Descriptive statistics

Demographic variable	***N***	**%**
Gender		
Female	87	59.7
Male	129	40.3
Education level		
High School Graduate	26	12
University Degree (undergraduate)	118	54.6
Higher Education (Masters/Doctoral)	72	33.3
Working Experience		
1 – 9 Years	44	20.4
10 – 19 Years	97	44..9
20 – 39 Years	47	21.8

30+ Years	28	13
Job Level		
Senior Management	30	13.9
Middle Management	112	51.9
Intermediate	72	33.3
Entry Level	2	.9

4.7 Analysis technique

Data from the completed surveys were exported directly to the IBM Statistical Package for the Social Sciences (IBM SPSS®) statistical analysis software. The dataset were screened for outliers and cases with significant amounts of missing data prior to entering data in IBM SPSS®. IBM SPSS® was used because it can perform regression analysis of the relationship between independent variables and the dependent variable to test and verify the research hypotheses. Demographic data that were measured as continuous variables were analyzed using descriptive statistics (means and standard deviations), and for ordinal and nominal demographic variables only frequency tables were produced. In addition, Hayes PROCESS SPSS Macro was used for moderation and mediation testing. The PROCESS Macro, which adopts bootstrapping technique, can generates bootstrapping confidence intervals for mediational and calculate direct and indirect effects (Hayes, 2017).

4.8 Validity and reliability

Validity is defined as the extent to which a concept is accurately measured in a quantitative study. It looks at whether the instrument adequately covers all the content that it should with respect to the variable. Whereas, reliability, or the accuracy of an instrument is the extent to which a research instrument consistently has the same results if it is used in the same situation on repeated occasions (Heale and Twycross, 2015). Content validity concerning the substance of the items under each construct was not a major concern due to the acceptable results of the pilot study. Content validity was achieved through a comprehensive review of the relevant literature as well as consultation with experts and practitioners. Moreover, the survey was sent to employees with enough knowledge about the phenomenon under study, i.e., Big Data and EP practices in government organizations. Further, we introduced a qualification question in the beginning of the survey to make sure that participant who don't meet the criteria are disqualified. Finally, to ensure reliability, the data were entered in SPSS no less than four times to confirm that the data entered are correct and results are the same.

The key principle of research hypothesis used in the current study rest on the validity of the constructs. Construct validity is evaluated by investigating what qualities a test measures, that is, by determining the degree to which certain explanatory concepts or constructs account for performance on the test. (Messick, 1993). To do that, Cronbach's alpha (α) values were calculated for each of the scales used using SPSS. Cronbach's α is a measure of internal consistency–in other words, it measures the extent to which a respondent answers items in a consistent manner (Gall *et al.*, 2003). Finally, discriminant validity was evaluated by calculating the intercorrelations between subscales of the five instruments using bivariate correlation analysis (Pearson's *r*).

4.9 Ethical considerations

After receiving an approval from Abu Dhabi University (ADU), to proceed with the study, the ethical standards and policies of their Institutional Review Board (IRB) were ensured during data collection. No sensitive data were collected. Further, during data collection process, consent was collected from each participant, to assure their privacy and confidentiality. It was made clear to them prior to filling the survey that they were not coerced into participation, and they were aware of the option to leave the study at any time without consequence. Additionally, to further ensure participant confidentiality, coding was assigned to participants by SurveyMonkey® and no personal information besides demographic data was gathered from participants.

The data from SurveyMonkey® and from the IBM SPSS® software was stored on a password-protected desktop computer. Only the researcher had access to the password. The data was backed up on a USB storage device, which was locked in a safe with a password combination. Finally, this study could be affected by method bias. Method bias from knowledge bias is based on the reasonable assumption that a person's knowledge will remain fairly stable during the measurement process which involves self-reported questionnaires; hence, may guess the hypothesis (Burton-Jones, 2009). To avoid method bias, the questionnaire items were randomized.

4.10 Chapter summary

The purpose of this study was to investigate the relationships between HC TC, and DDC on ENP under the mediation influence of EP. To address this purpose, the researcher collected data from procurement professionals or managers working in Abu Dhabi-based government entities. The data collection was secured using SurveyMonkey®. Prior to conducting the main study, a pilot study was conducted on one entity to assess the feasibility of study and tools used. Next, Statistical power analysis was performed in order to find the required sample size for determining the minimum sample to be statistically significant at a certain level. It was followed by the explanation of data collection procedures along with sample characteristics and survey-based research methodology. In the analysis techniques section, the statistical tools employed are discussed for this study using IBM SPSS® and Hayes PROCESS SPSS Macro (Hayes, 2017). Next chapter will focus on data analysis and results in relation to the research conceptual model and hypotheses.

CHAPTER V. RESULTS

This chapter reports the results of the different statistical analyses discussed in Chapter 4. Initially the results of factor analysis and scale reliability analysis are reported. Then, the results of linear regression from SPSS are presented. Finally the Hayes (2017) mediation, moderation, and conditional process analysis using PROCESS macro are reported followed by the summary of results chapter in the last section.

5.1 Factor structure analysis

The key premise of research hypothesis used in the current study rest on the validity of the constructs. The content validity concerning the substance of the items under each construct is not a major concern. The survey to procurement professionals in the targeted UAE public organization employees clearly indicating that they must with enough knowledge about the phenomenon under study. Further, the survey tool introduced a qualification question in the beginning of the survey to make sure that participant who do not meet the criteria are immediately disqualified and taken to the end of survey. Construct validity was determined by looking at the correlations among the variables. Convergent validity was determined through factor analysis. Both convergent and discriminant validity are also included in construct validity.

The scale items used in the study were factor analyzed using principal component analysis employing maximum likelihood and varimax rotation. Principal components analysis was used because the primary purpose was to identify and compute composite scores for the factors. Initially, the factorability of the 37 items was examined in a five-factor solution. However, initial results revealed that some survey items scored way below .40. Furthermore, each of the third, fourth, and fifth factor explained less than 3% of the variance. After eliminating items that did not contribute to a simple factor structure and failed to meet a minimum criterion of having a primary factor loading, the final five factor solution was preferred. For the final stage, principal components analysis of 28 items using varimax rotation yielded four factors that explained 63.46% of the total variance. The eigenvalues associated with each of the four factors were greater than 1.00. Bartlett's test for sphericity was significant

3588.881 (significance = 0.000). The Kaiser – Meyer – Olkin (KMO) measure of sampling adequacy was .885 that is high and above the commonly recommended value of .6 (Kaiser, 1974)

Results of factor analysis are reported in Table 5-1. The first factor had high eigenvalue (9.788) and explained 34.96% of the variance. The communality for the items was between 0.48 and 0.80, indicative of a high degree of linear association among the items of the scale. The four factors have theoretical support – HC, TC, DDC, and EP, - have been theorized to be unique and independent and can be linked to the construct of ENP.

Table 5- 1 Factor analysis results

	Component					**Communalities**
	1	2	3	4	5	
The e-procurement system ensures orders are processed quickly		.765				.705
The e-procurement system ensures orders get to suppliers quickly		.617				.564
The e-procurement system reduces the lead time of orders		.670				.625
The e-procurement system ensures that orders arrive on time		.582				.511
The e-procurement system has the right number of suppliers loaded		.609				.539
The e-procurement system is always available		.709				.636
The e-procurement system moves quickly from one screen to the next		.712				.586
The e-procurement system allows easy navigation through the order process		.769				.710
We have achieved a reduction of pollution and waste			.738			.607

We have improved compliance with our organization environmental policy		.592		.497
We have increased the level of recycling		.691		.601
We have preserved the environment		.757		.718
We have improved the environmental reputation of our organization		.679		.696
We have improved the overall environmental performance of our organization		.709		.756
Procurement managers are capable of working with other managers, customers, and suppliers to define opportunities that big data could bring to our organization	.652			.625
Procurement managers can anticipate the future business needs of the other functional managers, suppliers and customers using big data	.610			.532
Procurement managers are capable of understanding and evaluating the output produced from big data	.656			.571
We hire new staff that already have big data and predictive analytics skills	.699			.531
Procurement staff has right skills on big data analysis to accomplish their jobs successfully	.790			.742
Procurement staff has suitable education on big data analysis to fulfill their jobs	.771			.686
Procurement staff is well trained on big data analysis	.756			.715
We have access to huge, fast-moving, and unstructured data for procurement analysis			.419	.478
We have explored or implemented parallel computing methods to big data processing			.795	.722
We have explored or implemented various data visualization instruments in our e-procurement platform			.782	.734

We have explored or implemented new types of databases in our e-procurement platform				.768		.727
Our organization treat data as a tangible asset					.625	
In our procurement department we make our procurement decisions based on data rather than intuition					.807	
We are prepared to reverse our own intuition when data disagree with our viewpoint on procurement decisions					.762	
Note.						
Eigenvalues	9.788	2.717	2.225	1.532	1.505	
% of total variance explained	34.96%	9.70%	7.95%	5.47%	5.38%	
Total variance explained		44.66%	52.61%	58.08%	63.46%	

5.2 Reliability analysis

The reliability analysis is conducted to measure internal consistency and is reported using Cronbach's alpha. The reliability score (Cronbach's alpha) of EP scale is 0.869, ENP scale is 0.863, HC scale is 0.894, TC scale is 0.836, and DDC scale is 0.709. They follow the recommended criteria that Cronbach's alpha values above 0.7 indicate sound and reliable measures (Nunnally, 1978). The reliabilities of the scale items to total correlation, number of scale items, and scale reliability are presented in Table 5-2.

Table 5- 2 Scale reliability results

Component	**Item-to-Total Correlation**	**No of Items**	**Cronbach's Alpha**
E-procurement		8	0.869
The e-procurement system ensures orders are processed quickly	.684		
The e-procurement system ensures orders get to suppliers quickly	.564		

The e-procurement system reduces the lead time of orders	.617		
The e-procurement system ensures that orders arrive on time	.576		
The e-procurement system has the right number of suppliers loaded	.576		
The e-procurement system is always available	.653		
The e-procurement system moves quickly from one screen to the next	.623		
The e-procurement system allows easy navigation through the order process	.704		
Environmental Performance		6	0.863
We have achieved a reduction of pollution and waste	.577		
We have improved compliance with our organization environmental policy	.550		
We have increased the level of recycling	.590		
We have preserved the environment	.739		
We have improved the environmental reputation of our organization	.726		
We have improved the overall environmental performance of our organization	.780		
Human Capabilities		7	0.894
Procurement managers are capable of working with other managers, customers, and suppliers to define opportunities that big data could bring to our organization	.704		
Procurement managers can anticipate the future business needs of the other functional managers, suppliers and customers using big data	.627		
Procurement managers are capable of understanding and evaluating the output produced from big data	.657		
We hire new staff that already have big data and predictive analytics skills	.548		
Procurement staff has right skills on big data analysis to accomplish their jobs successfully	.798		
Procurement staff has suitable education on big data analysis to fulfill their jobs	.743		
Procurement staff is well trained on big data analysis	.780		
Technological Capabilities		4	0.836
We have access to huge, fast-moving, and unstructured data for procurement analysis	.484		
We have explored or implemented parallel computing methods to big data processing	.711		

We have explored or implemented various data visualization instruments in our e-procurement platform	.759		
We have explored or implemented new types of databases in our e-procurement platform	.732		
Data-driven culture		3	0.709
Our organization treat data as a tangible asset	.470		
In our procurement department we make our procurement decisions based on data rather than intuition	.635		
We are prepared to reverse our own intuition when data disagree with our viewpoint on procurement decisions	.488		

5.3 Correlation

Correlation analyses were conducted to examine the relationship the various variables under this study using bivariate correlation analysis (Pearson's *r*). The mean, standard deviations and inter-correlations between variables are also presented in Table 5-3.

Table 5- 3 Results of correlation analysis

Construct	M	SD	1	2	3	4	5
1. E-procurement	3.606	0.6123	1				
2. Environmental performance	3.655	0.5717	.398**	1			
3. Human capabilities	3.037	0.6535	.472**	.557**	1		
4. Technological capabilities	3.309	0.7101	.390**	.574**	.544**	1	
5. Data-driven culture	3.549	0.6498	.380**	.361**	.431**	.338**	1

** correlation significant at $p > 0.01$

5.4 Hypotheses testing

5.4.1 Results of regression analysis

Linear regression analysis was performed on hypotheses H1, H2, and H5 to determine whether to accept them or not. Whereas H1 denoting e-procurement (EP) as dependent variables and technological capabilities (TC) as independent variable. H2 denoting e-procurement (EP) as dependent variables and human capabilities (HC) as independent variable. And in H5 environmental performance (ENP) was dependent variables and e-procurement (EP) was independent variable. The results of the regression analysis are shown in Table 5-4.

H1 predicted that TC in big data have a positive relationship with EP. Consequently, to analyze H1, a simple linear regression was calculated to predict EP performance based on TC, β = .390, *t* (214) = 13.576, $p < .001$. A significant regression equation was found (F (1, 214) = 38.446, $p <.000$), with R^2 of .152. The results indicate that TC can explain 15.2% of the variance in the EP measures. Hence, the regression equation for predicting EP from TC was:

$$EP = 2.50 + .336\ (TC)$$

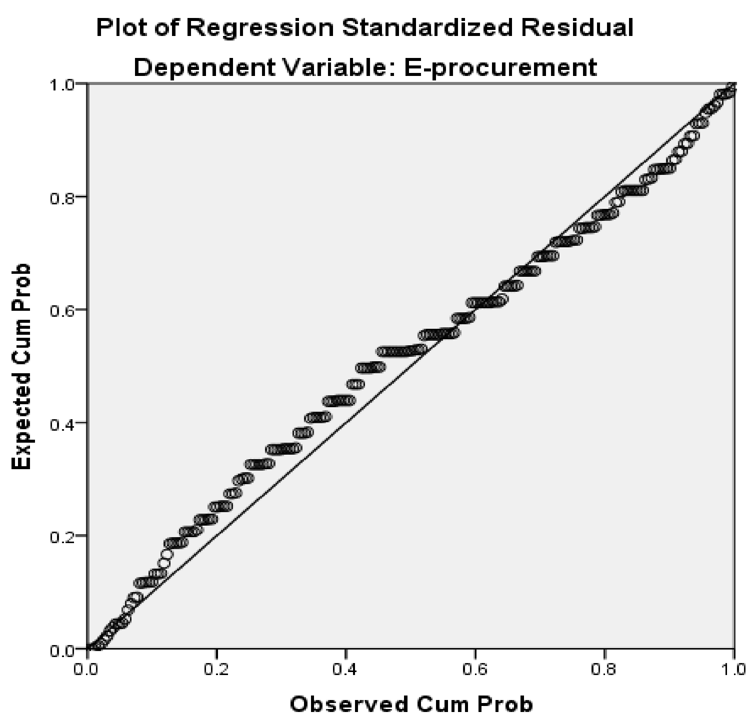


Figure 5. 1 Normality P-P plot for technological capabilities predicting e-procurement

H2 predicted that HC of big data have a positive relationship with EP, thus, to analyze this, a simple linear regression was calculated to predict EP performance based on HC, β = .472, *t* (214) = 12.897, $p < .001$. A significant regression equation was found (F (1, 214) = 61.50, $p < .001$), with R^2 of .223. The results indicate that HC can explain 22.3% of the variance in the EP measures. Hence, the regression equation for predicting EP from HC was:

$$EP = 2.26 + .443\ (HC)$$

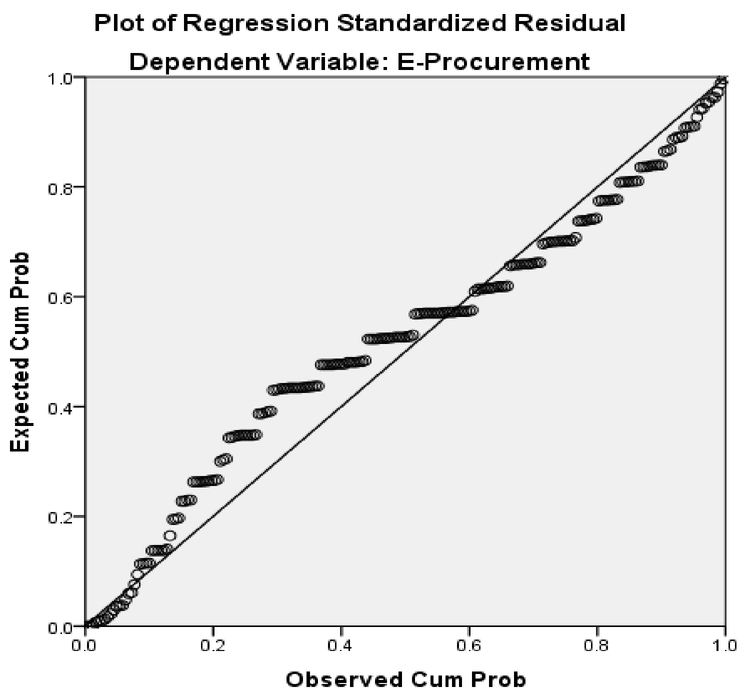


Figure 5. 2 Normality P-P plot for human capabilities predicting e-procurement

Lastly, H5 predicted that EP has a positive influence on organizations' ENP. Similarly, to analyze H5, a simple linear regression was calculated to predict ENP based on EP, β = .398, *t* (214) = 10.809, $p < .001$. A significant regression equation was found (F (1, 214) = 40.270, *p*

<.000), with R^2 of .158. The results indicate that EP can explain 15.8% of the variance in the ENP measures. Hence, the regression equation for predicting ENP from EP was:

$$ENP = 2.32 + .372\ (EP)$$

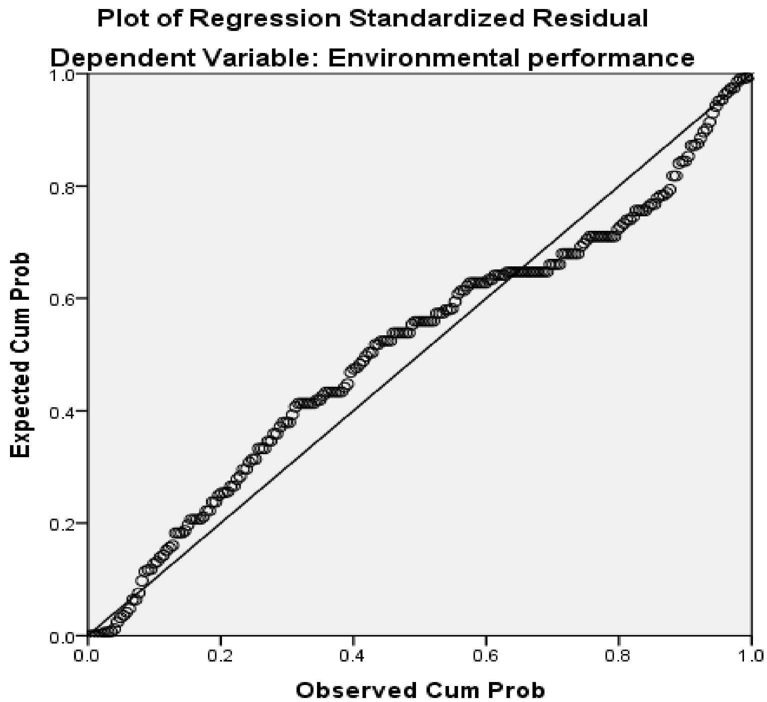


Figure 5. 3 Normality P-P plot for e-procurement predicting environmental performance

Table 5- 4 Linear regression results

Source	R^2	B	F	β	*t*	*p*	*Results*
H1. TC → EP	.152	.336	38.446	.390	13.576	.000	Supported*
H2. HC → EP	.223	.443	61.494	.472	12.897	.000	Supported*
H5. EP → ENP	.158	.372	40.270	.398	10.809	.000	Supported*

Note* Significance because $p < 0.005$

5.4.2 Indirect, and conditional process analysis

As discussed in chapter 4, Hayes PROCESS Macro (Hayes, 2017) is used to test the moderation and mediation effects of the conceptual framework constructs. In this analysis, as recommended by Hayes (2017), variables that are used to construct products are first mean centered prior to constructing their product in order to render the regression coefficients for those variables in tables provided interpretable within the range of the data. The decision to center or not has no effect on the value of the index of moderated mediation or inference about its size (Hayes, 2017). The bias corrected bootstrap confidence intervals are based on 5000 bootstrap samples. As illustrated by Hayes (2013), the bootstrap confidence interval gives a range of plausible values for the estimate. If the 95% confidence interval does not contain zero at the selected level of confidence, the result is statistically significant ($p < .05$). When the effect estimate deviates too far from zero, it counters the argument for chance as a plausible alternative explanation. Hayes (2017) PROCESS model 1 is used for simple moderation for H3 and H4, and model 4 is used for simple mediation analysis for H6 and H7.

5.4.2.1 Moderation

To investigate H3 a simple moderation model (PROCESS model 1) was utilized. The outcome variable for the analysis was EP. The predictor variable for the analysis was TC. The moderator variable evaluated for the analysis was DDC. The results in Table 5-5 showed that over all model is significant [$R^2 = .234$, $p < .001$]. However, the interaction between TC and DDC was found to be not statistically significant [$b = .038$, 95% CI (-.015 .091), $p = .164$] as presented in Table 5-6. The conditional effect of TC on EP showed significance [$b = .260$, 95% CI (.103, .418), $p < .005$]. At low moderation DDC = -1.950, the [conditional effect .187, 95% CI (.030, .343), p = .019]. At middle moderation DDC = .000, the [conditional effect = .260, 95% CI (.103, .418), p

< .005]. At high moderation DDC = 1.950, the [conditional effect = .333, 95% CI (.118, .550), p < .005]. The moderation model showed no significant results, hence, the moderation between TC and EP cannot be supported.

Table 5- 5 Moderation total effect summary

Source	*R*	*R-eq*	*MSE*	*f*	*df1*	*df2*	*p*
H3. TC → (DDC) * EP	.483	.234	.291	14.821	3.000	212.000	.000
H4. HC → (DDC) * EP	.520	.271	.277	19.648	3.000	212.000	.000

dependent variable: EP

Table 5- 6 Coefficients of moderating regression for H3

Model	*Coff(b)*	*Se*	*T*	*P*	LLCI	ULCI	Results
Constant	3.589	.042	85.358	.000	3.506	3.672	
DDC	.096	.032	2.962	.0034	.032	.140	Not Supported*
TC	.260	.080	3.263	.0013	.103	.418	
Int_1	.038	.027	1.396	.164	-.015	.091	

Note * Not significance due to *p* > .005 and 0 sets within the 95% confidence bootstrap interval

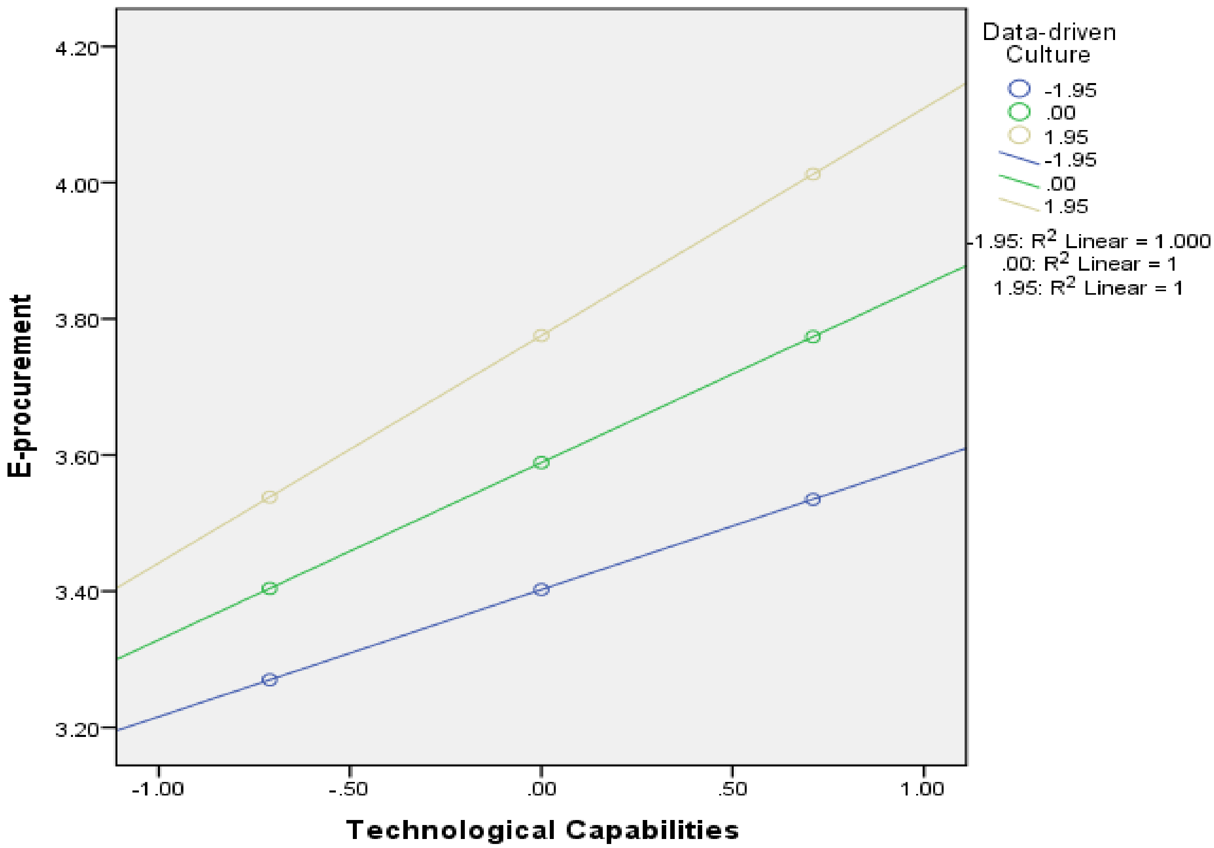


Figure 5. 4 Simple slopes equations of the regression of the moderation DDC effect on the relationship between TC and EP

Similarity, to investigate H4 a simple moderation model (PROCESS model 1) was utilized. The outcome variable for the analysis was EP. The predictor variable for the analysis was HC. The moderator variable evaluated for the analysis was DDC. The results in Table 5-5 showed that over all model is significant [R^2 = .271, p < .001]. However, the interaction between HC and DDC was found to be not statistically significant [b = .037, 95% CI (-.022, .096), p = .216] as presented in Table 5-7. The conditional effect of HC on EP showed significance [b = .411, 95% CI (.248, .573), p < .001]. At low moderation DDC = -1.950, the [conditional effect = .267, 95% CI (.120, .414), p < .001]. At middle moderation DDC = .000, the [conditional effect

= .340, 95% CI (.196, .482), p < .001]. At high moderation DDC = 1.950, the [conditional effect = .411, 95% CI (.212, .610), p < .001]. The moderation model showed no significant results, hence, the moderation between HC and EP cannot be supported.

Table 5- 7 Coefficients of moderating regression for H4

Model	*Coff(b)*	*Se*	*T*	*P*	LLCI	ULCI	Results
Constant	3.508	.037	93.936	.000	3.434	3.582	
DDC	.059	.027	2.136	.033	.004	.114	Not Supported*
HC	.411	.082	4.977	.000	.2479	.573	
Int_1	.037	.030	1.242	.215	-.022	.098	

Note * Not significance due to *p* > .005 and 0 sets within the 95% confidence bootstrap interval

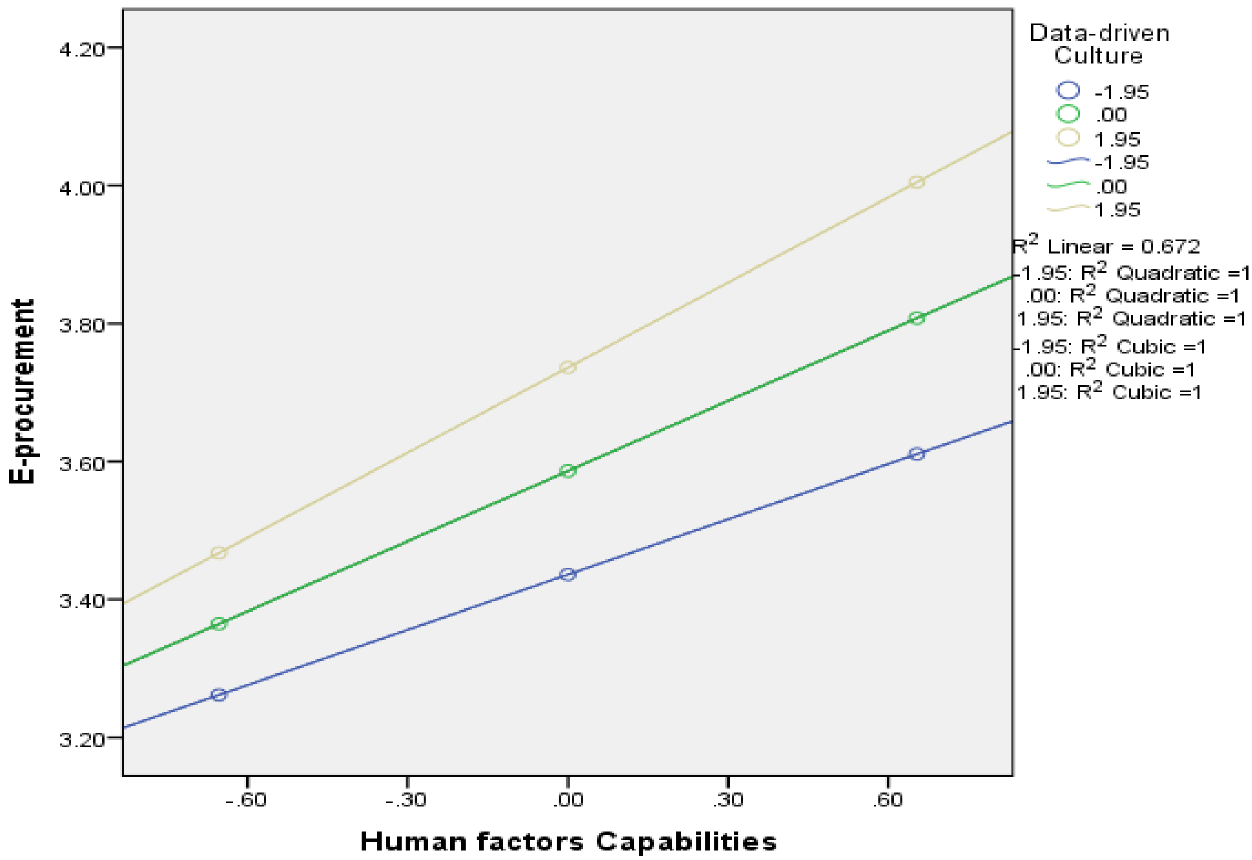


Figure 5. 5 Simple slopes equations of the regression of the moderation DDC effect on the relationship between HC and EP

5.4.2.2 Mediation

Before testing for mediation, it was important that the criteria used to measure the mediation in this research is described. It is believed that mediation occurs if the independent variable is responsible for a specific change in the mediating variable, which should also be responsible for the change in the dependent variable. According to Baron and Kenny (1986) and Kenny *et al.* (1998), mediation happens if (a) changes in the independent variable significantly responsible for changes in the mediator, (b) changes in the mediating variable significantly responsible for changes in the dependent variable, (c) changes in the independent variable significantly responsible for change in the dependent variable; and (d) the impact of the independent variable on the dependent variable significantly decreases when the mediating variable is included in the third equation. In a simple mediation model (PROCESS model 4), a mediator variable M influences the relationship between antecedent variable X and the outcome variable Y. In this study H6 predicted that TC under the mediation effect of EP has an influence on ENP. Meanwhile, H7 predicted that HC under the mediation effect of EP has an influence on ENP.

To investigate H6, a linear regression was performance to determine the independent effect of TC on EP, the independent effect of TC and ENP and the independent effect of EP on ENP. The results revealed that the relationship between TC and EP was significant (.336, $p < .001$); the relationship between TC and ENP was significant (.462, $p < .001$); and it was established previously that the relationship between EP and ENP was also significant (.372, $p < .001$). Then, a simple mediation analysis was performed using PROCESS Macro. Whereas. the predictor variable was TC, the outcome variable for the analysis was ENP, and the mediator variable was EP. As Figure 5.6 illustrates, the regression coefficient between TC and EP was statistically significant (.337, $p < .001$). The direct effect of TC on ENP was .397 ($p < .001$). However, when EP introduced as a mediator, the regression coefficient between EP and ENP remained significant (.192, $p < .05$). On the other hand, the total indirect effect (indirect effect of TC on ENP through EP) was .065, 95 % CI [.022, .127]. CI not included zero, thus indicating that the mediation effect was statistically significant as suggested by Preacher and Hayes (2008). Hence, the result indicates that TC was a significant predictor of ENP and EP is was a significant predictor for ENP, and the effect of EP on the TC-ENP is also significance. Those results support the mediation hypothesis. In addition, since the effect of TC to ENP did not drop to 0 when introduced EP as a mediator, it can be concluded that this is partial mediation.

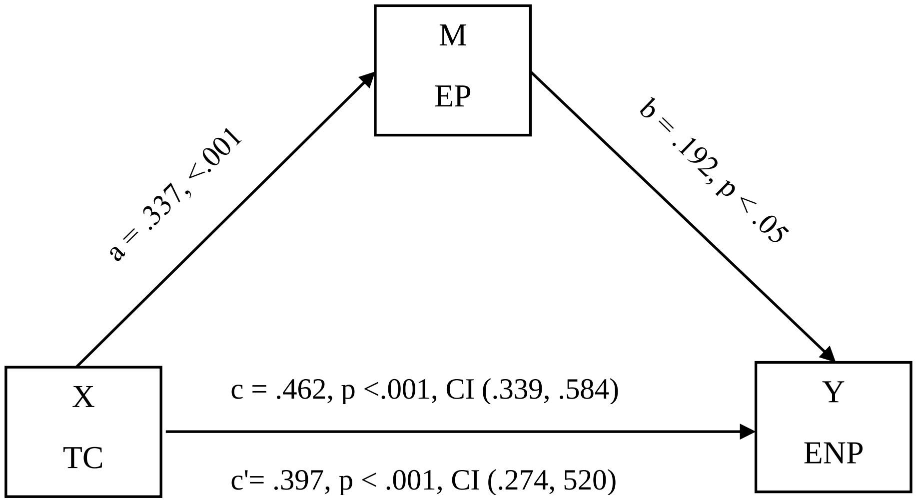


Figure 5. 6 Results of mediation analysis of H6

To investigate H7, a linear regression was performance to determine the independent effect of HC on EP, the independent effect of HC and ENP and the independent effect of EP on ENP. The results revealed that the relationship between HC and EP was significant (.443, $p < .001$); the relationship between HC and ENP was significant (.448, $p < .001$); and the relationship between EP and ENP was also significant (.372, $p < .001$), Secondly, a simple mediation analysis was performed using PROCESS Macro. Whereas, the predictor variable was HC, the outcome variable for the analysis was ENP, and the mediator variable was EP. As Figure 5.7 illustrates, the regression coefficient between HC and EP was statistically significant (.443, $p < .001$). The direct effect of HC on ENP was .412 ($p < .001$). However, when EP introduced as a mediator, the regression coefficient between EP and ENP dropped and became not significant (.162, $p = .070$). On the other hand, the total indirect effect (indirect effect of HC on ENP through EP) was .072, 95 % CI [.007, 1.724]. CI not included zero, thus indicating that the mediation effect was statistically significant as suggested by Preacher and Hayes (2008).

Hence, the result indicates that HC was a significant predictor of ENP and EP was a significant predictor for ENP, but the effect of EP on the HC-ENP is not significant. Those results did not support the mediation hypothesis and shall be discussed further in the next chapter.

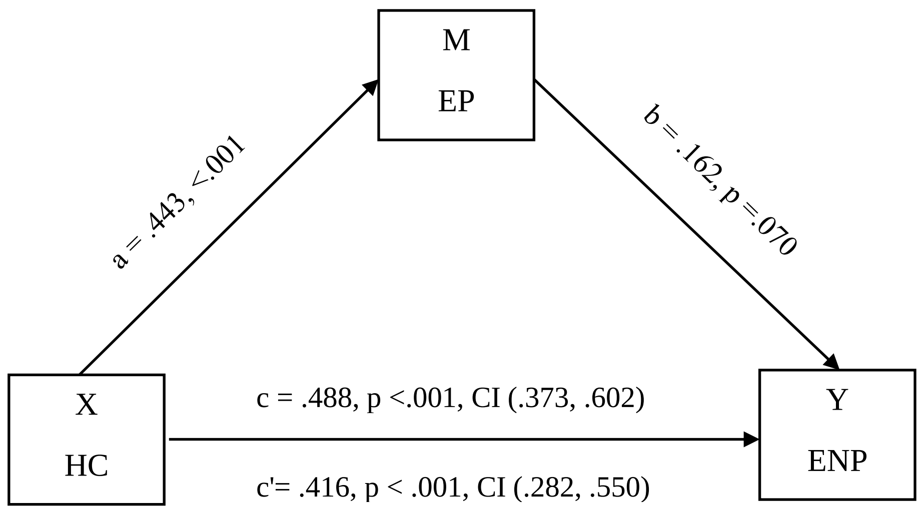


Figure 5. 7 Results of mediation analysis of H7

5.5 Conclusion

This chapter presented the analyses of data collected to assess the degree to which big data capabilities (TC and CH) impact ENP via EP in the public sector. The first step in this analysis was to conduct a descriptive analysis and check the frequencies of the variables used in this study. Next, the results of factor analysis and scale reliability analysis was reported presented. Cronbach alpha was used to test reliability for the constructs. Then this chapter tested the hypotheses understudy utilizing Hayes (2017) mediation, moderation, and conditional process analysis using PROCESS macro. The results as summarized in Table 5-8 revealed that H1, H2 and H5 was supported, and H3, H4, H7 was not supported. Whereas H6 was partially supported.

Chapter 5 will provide additional discussion of the major findings, practical implications, limitations, and recommendations future research.

Table 5- 8 Summary of results

H#	Hypothesis statement	Results
H1	TC have a positive relationship with EP performance.	Supported
H2	HC have a positive relationship with EP performance.	Supported
H3	DDC positively moderates the relationship between TC and EP performance	Not supported
H4	DDC positively moderates the relationship between HC and EP performance	Not Supported
H5	EP has a positive influence on organizations' ENP	Supported
H6	TC under the mediation effect of EP have an influence on ENP	Supported (partial mediation)
H7	TC under the mediation effect of EP have an influence on ENP	Not supported

CHAPTER VI. DISCUSSION, IMPLICATIONS, AND CONCLUSION

The literature review demonstrated the importance of this study and that employing big data can establish a framework for sustainability in the ICT infrastructure, such as EP platforms, and in organizations, which could reduce their overall environmental impact and unlock new efficiencies to improve GPP. The four research questions guiding this study were inspired by recent big data studies' recommendations (e.g., Chidambaram *et al.* (2015) Mikalef *et al.* (2019a)) suggesting that almost every organization already has the necessary resources and capabilities to implement big data in their procurement function and that 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.

This study utilized RBV, NRVB, and DC to conceptualize seven hypotheses aimed to link the relationship between big data capabilities (TC and HC), DDC, EP, and ENP and answer the research questions. This chapter contains a discussion of the results presented in the previous chapter, significance of the implications, limitations of the research, recommendations for future studies, and a conclusion.

6.1 Discussion

6.1.1 The influence of big data on e-procurement

The first question of this study was, "What is the influence of big data capabilities (TC and HC) on public organizations' EP performance?" To answer the first research question, two hypotheses were developed. The key underpinning of these hypotheses is the argument that organizations that employ higher degrees of big data are in a better position to have a better EP performance output and achieve a better competitive advantage.

The first hypothesis (H1) proposed that the TC of big data have a positive relationship with EP. As expected, the results showed a significant regression relationship between TC and EP, lending to accepting the hypothesis. As suggested previously, big data technology enables utilization of real-time data to generate huge insights for predictions, which can provide sufficient business intelligence to the public procurer to perform and act with better agility and make smarter and more accurate decisions about spending, managing suppliers, and developing stronger procurement strategies (Hickey, 2018; Rane et al., 2019). This is in line with recent studies demonstrating the effectiveness of disruptive technology such as big data and blockchain in various supply chain domains (Mubarik et al., 2019; Thio-ac et al., 2019). This result adds to their recent work, demonstrating that the same is true for the procurement function, which was hardly addressed in previous literature.

The second hypothesis (H2) proposed that HC of big data have a positive relationship with EP. Similarly, the results showed a significant regression relationship between HC and EP, leading to accepting this hypothesis. Although recent studies have highlighted the importance of HC in big data (Dubey *et al.*, 2019; Gupta and George, 2016; Mikalef *et al.*, 2019a, 2019b), this is the first study to address its importance to EP. This is in line with previous research that found that HC of big data were crucial in any type of ICT-based business transformation (Daniel and Wilson, 2003; Wang, Y., 2009). This idea was also highlighted by Hickey (2018), who suggested that to unlock big data's potential in procurement operations, organizations must focus on training and recruiting the most appropriate candidates. HC in big data is considered "a challenge to academia," according to (Colegrove and Peters, 2017). They recommended that governments, industries, and the academic community work together to create better human capability by providing education for the higher level skills and abilities required across roles in industries to assure that no one gets left behind in the new big data age.

Although several private organizations in other countries have applied big data technology in different areas in the supply chain, including procurement, some argue that public usage of this type of technology is still far away (Thio-ac et al., 2019). Hence, these findings prove that big data technology can indeed improve EP in the public sector, and public procurement leaders must immediately take advantage of this emerging technology, as it has the potential to improve public procurement in the future (Handfield et al., 2019).

6.1.2 The role of data-driven culture

The second research question was, "What is the impact of a data-driven culture (DDC) on the relationship between big data capabilities and EP in the public sector?" Two hypotheses were proposed to answer this question. These hypotheses argue that organizations with a greater DDC will have a higher EP under the big data environment. The third hypothesis (H3) proposed that DDC positively moderates the relationship between TC and EP, and the fourth hypothesis (H4) proposed that DDC positively moderates the relationship between HC and EP. The results indicated a nonsignificant moderation effect of DDC on the relationship between big data capabilities (TC and HC) and EP. Hence, both hypotheses were rejected.

Although this study did not prove the moderation impact of DDC between big data capabilities and EP, DDC is still an important driver for big data transformation. Looking at the results from firms' competitive advantage prospective, many have argued that DDC might be the most essential intangible resource for a firm to gain improvement in its data-driven supply chain (Arunachalam et al., 2018; Brinch, 2018; Jeble et al., 2018). In fact, DDC is also considered the key driver to implement and gain sustainable advantage from big data technology (Sjusdal and

Lunde, 2019). However, this result indicates that this could not be the case for EP in the UAE public sector. The UAE organizations under study are currently collecting masses of data, but it could be that only a small percentage of organizations have benefited from their big data analytic investments. This might be because in the case of developed country such as the UAE, organizations still rely on the experience and/or intuition of their managers and employees to make procurement decisions, as highlighted by (Gupta and George, 2016). It could also be that top management does not value data-driven decisions and makes all procurement decisions independently. Whatever the case, DDC is becoming important in private organizations, and it could be some time before DDC becomes relevant in the UAE public sector.

6.1.3 The impact of e-procurement on environmental performance

The third research question discussed the relationship between EP and ENP in the public sector. The literature review revealed that not many studies have investigated this relationship, which can be considered a missed opportunity to deeply understand this relationship and build on it. Hence, this study utilized NRBV and DC theories to formulate the fifth hypothesis (H5) that suggested that EP has a positive influence on organizations' ENP. The idea behind this premise is that any organization with higher EP performance should consequently achieve higher ENP. As expected, the results showed a significant regression relationship between EP and ENP, lending to accepting the hypothesis. This finding support previous literature by Walker and Brammer (2012) suggesting this relationship exists. EP does not support sustainability and environmental performance by simply changing from paper-based to electronic-based procurement and saving more trees. EP can be an extremely valuable tool to promote the green agenda at the strategic and tactical level of procurement, from the initial procurement stage to disposal. It enables a broad pattern for market readiness evaluation and a consolidated EP system designed for adequate GP monitoring and assessment (Lăzăroiu et al., 2020).

6.1.5 The influence of big data on e-procurement and environmental performance

This leads to the main and final research question that put everything together regarding how to make EP greener. The fourth question was, "What is the influence of EP on the relationship between big data capabilities (TC and HC) and ENP in the public sector?" Two hypotheses were proposed to answer this research question. These hypotheses argue that organizations that uses big data technology within their EP system have improved ENP and ultimately achieve green EP.

Hypothesis 6 (H6) proposed that TC, under the mediation effect of EP performance, influences ENP. The results revealed that TC has a significance positive influence on ENP, and when EP was introduced as a mediator, ENP improved even further. Hence, it can be concluded that TC of big data, such as availability of data and data infrastructure, must be utilized in organizations' EP systems to achieve higher ENP. This finding makes sense from a technology perspective. Researchers have suggested that using the traditional ICT infrastructure to implement big data technology is not possible due to the 5V properties of big data. Organizations, therefore, must significantly improve the existing ICT systems to allow for managing big data economically and efficiently (Gandomi and Haider, 2015; Lnenicka and Komarkova, 2019; Shi, Z. and Wang, 2018). This is also the case with ICT-based procurement. Once an organization enters the data-driven procurement era, it needs to transform the infrastructure of its EP system to gain the most from it, achieve competitive advantage, and save money. Unfortunately, organizations have increasingly looked to technologies such as cloud computing and BDA to renovate everything from human resources, marketing, and sales to supply chain management, while ignoring the procurement function (Ruehle, 2018). There is a good opportunity now for the public sector to learn this lesson from the private sector and invest in sophisticated ICT infrastructure such as cloud computing, big data systems, No-SQL database, cognitive systems, deep learning, and other artificial intelligence techniques, so they can quickly catch up with and even surpass the private sector.

Hypothesis 7 (H7) proposed that HC under the mediation effect of EP performance influences ENP. The results revealed that HC has a significance positive influence on ENP. However, there was no significant relationship when EP was introduced as a mediator. Although there is significant theoretical evidence that support this hypothesis, in this study, it could not be accepted. This could be due to the status of intangible big data capabilities such as experience and technical skills in the UAE public sector. According to RVB, HC resources comprise of employees' knowledge, experience, problem-solving abilities, leadership qualities, relationships with others, and business acumen (Barney, 1991). In fact, DC theory suggests that HC are of huge relevance in learning to generate new business insights, thus helping organizations gain new opportunities and achieve higher performance (Eisenhardt and Martin, 2000; Xu and Kim, 2014). In different settings, such as more advanced government or the private sector, this hypothesis could be accepted. However, this is not the case in the UAE public sector because it just started implementing big data; hence, intangible human capabilities are still lacking and could take years to build and flourish. This finding is aligned with the previous finding regarding the insignificant impact of DDC. However, governments need to develop a human resource BDA strategy that consists of recruitment, planning, training, informing, and employee involvement in the implementation of BDA in the procurement function, as Popovič et al. (2018) suggested.

6.2 Implications

6.2.1 Theoretical implications

This study has several theoretical implications for BDAC research. First, it is among the first studies to assess the impact of big data capabilities (technological and human capabilities) on ENP and EP and evaluate the moderation impact of DDC on the relationship between big data capabilities and EP. Although there is an extensive literature on big data capabilities, EP, and ENP, research on integration of the three constructs is scant. Second, the current study utilized the DC framework to view the construct of big data capabilities as multidimensional, integrating the technical, human, and cultural perspectives. The extant literature has predominantly viewed the relationship between ICT-based procurement and big data as a technical construct (Fu et al., 2019; Handfield et al., 2019; Mathew, 2019; Thio-ac et al., 2019). The DC framework allows any organization to adapt both internally and externally to the surrounding environment (Teece et al., 1997). Such capabilities provide the transparency level needed in procurement to increase organizational performance and achieve goals (Teece et al., 1997). Thus, our study contributes to the emerging literature on big data by advancing the theoretical understanding of BDAC in relation to ICT-based procurement and environmental science via the DC framework.

Third, this integrative approach also provides a more nuanced understanding of big data and its complex relationships with EP and ENP. This contribution is particularly important because it opens up the dialogue for researchers to consider employees' involvement in big data projects through a bottom-up process to enable data-driven green procurement decision-making, not just through a top-down process. Finally, this study's findings show that in fact, individual dynamic capabilities can work well independently to create green EP for an organization; however, these capabilities must work in harmony and complement each other to work effectively and produce the desired impact. This should create a debate in academia on whether the DC framework is best suited when studying big data capabilities in the field of environmental management, as other RVB extensions, such as the resource orchestration theory (ROT), could be more suitable (Hitt et al., 2011; Sirmon et al., 2011).

6.2.2 Practical implications

Our findings can provide guidance to managers and consultants engaged in implementing big data technology in firms. Technological innovation in big data, ICT-based procurement, sustainability, and automation have challenged the traditional government approach to innovation, and many are looking for ways to reinvent their operation to compete with the private sector and stay relevant. The finding that big data capabilities (technological and human capabilities) strongly influence firms' EP and ENP indicates that to translate big data applications into overall firm performance, managers need to concentrate on building strategies focused on technological and human capabilities, which includes big data infrastructure, data availability, technical skills, and managerial skills. Such activities are conducted in the planning phase of transforming to data-driven EP systems at the strategic level of procurement.

Furthermore, according to this study, to create DDC, employees need to understand how they fit in to both the decision-making process and procurement function in the big data environment. This can be considered a human resources issue. According to Prieto and Revilla (2006), learning is considered an important dynamic capability to achieve higher performance and should be viewed as a "high order capability," and human skills are of huge relevance to learning; their value depends upon their employment, in particular in organizational settings (Eisenhardt and Martin, 2000). In the supply chain, human resources management is considered part of procurement planning and should be involved in the beginning of the procurement process (Lengnick-Hall et al., 2013). This study showed that in the big data environment, procurement employees at all levels in an organization are required to make some decisions, regardless of their job titles, and have the ability to make good decisions grounded in tangible evidence as suggested from data. Hence, employees and managers must be able to handle the technological components and analytical requirements of big data and recognize the value of big data to understand where to apply insight efforts. The implication of this research is that in big data applications, organizations must focus on big data-specific technical and managerial skills so employees can understand where they fit into the organizational value chain and procurement planning to create data-driven culture and deliver better overall organizational performance.

6.3 Limitations and future research

We believe that our model is sound and firmly grounded in well-established theory, and we tested it with reliable survey instruments and data. Nevertheless, some limitations and unanswered questions must be acknowledged. First, the current study had a relatively small sample size of 216 from the UAE public sector. Future researchers could access a larger sample drawn exclusively from both the public and private sector for comparison. Second, this study only examined limited big data capabilities. It could be profitable to investigate other variables not included in this study, such as top management commitment, organizational learning, and procedural practice (Jeble et al., 2018; Mikalef et al., 2019b), or even to look at big data capabilities from a different perspective, 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 study were collected only in one country. Future researchers could expand this study by collecting data from more countries with different cultural backgrounds considering cultural factors (e.g., language, developed vs. developing countries). Finally, this study employed a cross-sectional research design for data collection. Hence, it would be useful to employ a case study or a longitudinal study to assess our proposed model better and capture its stability across time or settings.

6.4 Conclusion

Although studying big data 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 big data technology side, organizations must focus on assuring the interoperability of data infrastructure with other systems and applications, as well as the availability of accessible data to be used for analysis. Similarly, on the human side of big data, the focus should be 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 get the most out of big data and green procurement simultaneously by leveraging their ICT infrastructure, data, and human capital to achieve environmental performance.

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