JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2026, 11(1), 3019-3035
ISSN: 2589-1316

Factorial Big Data Analytics for Sustainable Public Procurement Practices

Thokozani Patmond Mbhele[1*], Emilia Ndeshipanda Salomo[2]

[1] *University of KwaZulu-Natal (Westville Campus), Discipline of Supply Chain Management, School of Commerce, Private Bag X54001, Durban, 4000, KZN Province, South Africa, Tel. no: +2731 260 7524, E-mail: mbhelet@ukzn.ac.za*, ORCID: *https://orcid.org/0000-0003-3124-8781*

[2] *University of KwaZulu-Natal, School of Commerce, Durban, South Africa. Email: emilysalmo@gmail.com*, ORCD: *https://orcid.org/0009-0007-0722-4153*

*__Corresponding Author:__ mbhelet@ukzn.ac.za

Citation: Mbhele, T. P. and Salomo, E. N. (2026). Factorial Big Data Analytics for Sustainable Public Procurement Practices, *Journal of Cultural Analysis and Social Change*, 11(1), 3019-3035. https://doi.org/10.64753/jcasc.v11i1.4623

Published: March 03, 2026

ABSTRACT

The epitome of sustainable public procurement practices aligns with the principles of transparency, integrity, competitiveness, and efficiency, underpinned by the growing adoption of big data analytics capabilities. Big data analytics (BDA) enhances supply chain visibility, operational efficiency, and risk management; however, it has become evident that public supply chains in developing nations require robust digital infrastructure to effectively leverage the potential benefits of BDA. The research objective is to establish the effective role of Big Data Analytics (BDA) in enhancing sustainable public procurement practices (SPPP), aligning with the objectives of the Namibian Procurement Act 2015. The research further evaluates the factors impacting the technological, organisational and environmental context of public procurement principles through data-driven insights on the view of economic constraints and inequalities. The descriptive quantitative research design is rooted in a positivist perspective, focusing on an empirical case study of Namibia to assess the impact of BDA within the Technology-Organisation-Environment (TOE) framework. The research design employs a descriptive case study, enabling the exploration of factorial interrelationships. Diverse perspectives are integrated via stratified sampling, resulting in a sample size of 270 administered for data collection. Inferential statistics, including multivariate analysis, were used to analyse the data. The study revealed enhanced public procurement practices following the enactment of the Public Procurement Act 2015. ICT infrastructure, data quality, and system scalability are pivotal for BDA integration, despite hindrances such as leadership commitment, procurement capacity, procedural complexities, and resource constraints, which impede the shift towards sustainable procurement. These findings culminate in a TOE framework, which suggests that BDA's adoption offers significant strategic value, including improved decision-making, increased efficiency, enhanced transparency, and improved supplier performance in procurement. BDA's strategic effective role/value influences its adoption, leading to the transformation of sustainable public procurement practices in Namibia. This model systematically outlines the impact of BDA adoption on public procurement, showcasing how the TOE factors shape BDA's success in achieving SPPP. This research provides policymakers, public procurement professionals, and technology providers with practical insights to enhance the strategic value of BDA for sustainable procurement. This study contextualises the interplay of TOE factors for BDA adoption in public procurement for developing nations.

Keywords: Namibia, Technology-Organisation-Environment factors, big data analytics, strategic value, sustainable public procurement practices.

INTRODUCTION

The imperatives of sustainable innovation are becoming increasingly pronounced due to escalating concerns over ecological and societal thresholds. Sustainable public procurement has also become a central concern for policymakers and scholars alike (Adjei-Bamfo et al., 2019). This resonant interest converges on the transformative capacity of sustainable procurement—a paradigm that seeks to integrate environmental, social, and economic considerations within the contours of public procurement practices. This convergence is particularly significant, considering the vast scale of public procurement activities that impart them with the potency to catalyse sustainable development (Nogues Comas & Mendes Dos Santos, 2021; UNSS, 2020). However, the extent to which such ambitious aspirations crystallise into actionable practices warrants closer examination (Adjei et al., 2019), especially given the backdrop of scepticism surrounding the alignment of procurement strategies with sustainable objectives (Nogues Comas & Mendes Dos Santos, 2021). The research study focuses on big data analytics and sustainable public procurement practices, utilising key literature, the technology-organisation-environment framework, and further analysing quantitative data using multivariate analysis.

Background and Research Problem

Sustainable public procurement practices require a transformative tool that necessitates an interdisciplinary approach to bridge the gap between sustainability imperatives and procurement practices (Rejeb et al., 2018). However, leveraging the real-time and diverse data streams requires the complete incorporation of these transformative digital technologies into procurement practices (Lenderink, 2019). BDA employs sophisticated analytical methodologies to uncover intricate trends, patterns, and correlations, providing insights that enrich informed decision-making (Schwab, 2018). In this context, public procurement, epitomised by its principles of transparency, integrity, competitiveness, and efficiency (Government Gazette, 2017), stands poised to gain significantly from BDA's capabilities. Nevertheless, integrating BDA within public procurement domains remains constrained and hindered by numerous factors (Hopwood, 2019), including data dispersion challenges that Namibia faces (Marenga, 2020).

In this complex interplay of sustainability imperatives, technological potentials, and procurement challenges, this study undertakes a journey to examine the effective role of BDA in facilitating sustainable public procurement practices (Kozanoglu et al., 2022; Klingler & Schooner, 2023). The study's entry point into this discourse is through a transdisciplinary prism—a viewpoint that seeks to unravel the intricate interdependence between technological propensities and the contours of sustainable procurement. The research objective is to establish the effective role of Big Data Analytics (BDA) in enhancing sustainable public procurement practices (SPPP), aligning with the objectives of the Namibian Procurement Act 2015. The research further evaluates the factors impacting the technological, organisational and environmental context of public procurement principles through data-driven insights on the view of economic constraints and inequalities. The research focuses on the nexus of BDA and sustainable public procurement within Namibia, a developing nation. Through this focused gap, the study is poised to deliver pragmatic insights on the technology-organisation-environment framework that resonate within the academic discourse and practical policy landscapes. It is also crucial to uphold the strategic value of BDA by factor analysing the interrelationships within technological development, organisational conditions, industry environment and sustainable public procurement adoption.

THEORETICAL FRAMEWORK

The study conceptual framework is grounded by the Technology-Organisation-Environment (TOE) framework, which has been widely employed to comprehend technology adoption across diverse contexts, such as the Adoption of Enterprise Resource Planning (ERP) solutions (Awa et al., 2016), environmental management information systems (Ibrahim & Jaafar, 2016), Information Systems (IS) adoption in small and medium-sized enterprises (SMEs) (Maroufkhani et al., 2022), cloud computing adoption and governance, and adoption of learning analytics in the UK education system (Saint & Gutierrez, 2017). TOE framework that outlines the process of innovation (Tornatzky & Fleischer, 1990). The TOE framework has also demonstrated its effectiveness in analysing the adoption of BDA in public procurement for sustainability (Kozanoglu et al., 2022). Sivarajah et al. (2020) strategically applied the TOE framework to identify the factors influencing the adoption of BDA in public procurement within the UK context. This study found that technological, organisational, and environmental factors are all interrelated and play a crucial role in shaping the trajectory of BDA adoption in the public procurement domain (Sivarajah et al., 2020).

The TOE framework's technological, organisational, and environmental components contribute to understanding the dynamics of BDA adoption. Technological factors in BDA adoption refer to the characteristics of BDA technologies, compatibility with existing systems, and perceived benefits. Organisational factors involve culture, leadership, and resources that influence BDA assimilation. In contrast, the environmental factors encompass regulations, market conditions, and collaborative opportunities that shape BDA adoption (Awa et al., 2017). Despite the TOE framework's strengths, some weaknesses include variability across different contexts and critiques of its simplicity. Despite these limitations, its consistent empirical support makes it an invaluable tool for understanding complex technology adoption, such as BDA (Aday & Aday, 2020; Alsetoohy et al., 2021). This study applied the TOE framework to analyse each identified factor in BDA adoption for SPPP comprehensively. The framework of technological advancements notably shapes the strategic value attributed to BDA, while organisational conditions impact the relationship between the industry environment and BDA's strategic significance. The study aims to investigate the relationships between BDA's strategic value and the actual adoption of SPPP, utilising rigorous statistical analysis to examine these variables and gain insights into their complex interplay and joint impact on promoting SPPP.

LITERATURE REVIEW

The pivotal role of BDA is earmarked to propel SPPP within the Namibian context. This exploration within scholarly discourse reveals how technological advancements redefine supply chains and procurement practices, transforming them with data-driven insights (Arrowsmith & Trepte, 2019; Biswas & Sen, 2017). These advancements, complemented by systems like e-procurement, underscore the growing influence of Artificial Intelligence (AI) technologies (Thakurta & Guha Deb, 2023). The transformative power of strategic procurement in national development becomes evident due to its role in expenditure management (Sönnichsen & Clement, 2020; Adjei-Bamfo & Maloreh-Nyamekye, 2019). Hence, strategic procurement reshapes markets, embedding sustainability criteria into public procurement (Arrowsmith & Trepte, 2019). The literature also underscores the symbiotic relationship between technological advancements and the promotion of SPPP. Yet, the discourse often overlooks the role of technological diversity in fostering SPPP (Grandia & Voncken, 2019). Despite the significance of BDA in optimising supply chains, its underutilization persists due to limited data availability and misconceptions about its value (Benzidia, Makaoui, & Bentahar, 2021; Adjei-Bamfo & Maloreh-Nyamekye, 2019). Thus, constructing a robust conceptual framework becomes imperative to comprehensively encapsulate BDA's role in enabling SPPP. Guided by the TOE framework, this study develops a framework that navigates the multifaceted realm of technology adoption within the context of public entities. Through this theoretical lens, the review captures the intricate dance of technological, organisational, and environmental factors that collectively shape the data and BDA landscape in SPPP (Ullah et al., 2021; Mohungoo, Brown & Kabanda, 2020).

Industrial Revolutions and BDA

The Industrial Revolution (IR) began in the 18th century, marking the start of Industry 1.0 and significant advancements in production efficiency and scale. Industry 2.0, in the 19th century, introduced electrical energy and mass production. Industry 3.0 introduced automation and mainframe computers in the 20th century, enabling the structured storage of data (Lee, 2017). Industry 4.0, also known as the Fourth Industrial Revolution (4IR), has introduced technologies such as smart manufacturing, AI, and the Internet of Things (Ivanova & Ivanov, 2020). The 4IR facilitated extensive data collection across supply chains, leading to the emergence of BDA (Mageto, 2021). Rapid growth in real-time and diverse digital data from IT activities has propelled the concept of big data (Gandomi & Haider, 2015), enabling the analysis of both structured and unstructured data in Industry 4.0 (Sharma & Pandey, 2020), as illustrated in **Figure 1**.

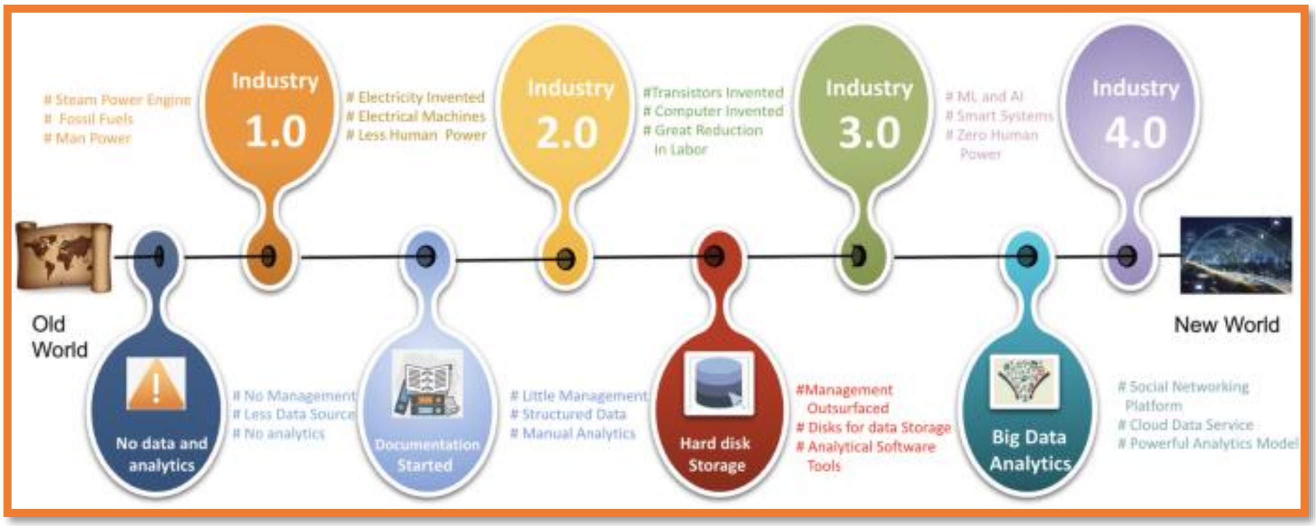

Figure 1: BDA in IR
Sources: Sharma & Pandey (2020).

Figure 1 highlights the accelerating pace of technological changes in the industrial environment. Cut-edge technologies brought evolutions such as the social web, BDA, and AI, significantly shaping industrial revolutions towards developing intelligent and sustainable industries (Sharma & Pandey, 2020). This IR evolution indicates that BDA adoption is inevitable in AI-driven global markets.

BDA adoption

As IR persist, BDA's significance lies in the foundation for the forthcoming digital ecosystem of the next revolution. However, limited research has explored the role of BDA in public procurement, while substantial literature has focused on its impact on supply chain management (SCM). Sustainable SCM emphasises recycling, cost reduction, and waste minimisation (Roman, 2017). BDA augments SCM by enhancing AI-aligned aspects, such as demand forecasting, risk management, and decision-making (Farooque et al., 2019). Thus, BDA's contributions to SCM, including improved supply chain visibility, operational efficiency, and risk management, are well-documented (Heidari, 2018; Moretto et al., 2017). However, a gap exists in understanding BDA's role in cognitive procurement, particularly in the public sector (Klingler & Schooner, 2023), as well as how BDA can empower sustainable public procurement (Kozanoglu et al., 2022).

The global challenges in developing nations underscored the BDA's intrinsic role in the realm of SCM, particularly in supporting the resilience of digital supply chains (Aday & Aday, 2020; Alsetoohy et al., 2021; Liu et al., 2022). In this context, it became evident that the public supply chains of developing nations require fortified digital infrastructure to effectively harness the potential benefits of BDA (United Nations, 2020). It is imperative to enhance digital capabilities to ensure the efficiency, adaptability, and sustainability of procurement practices within the socio-economic landscape of developing economies.

Public procurement can glean insights from SCM's effective integration of BDA. SCM's successes in decision-making (Farooque et al., 2019), supply chain visibility (Heidari, 2018), risk management (Moretto et al., 2017), efficiency enhancement (Mageto, 2021), and demand forecasting (Roman, 2017) offer valuable lessons for public procurement. Adopting BDA can enhance transparency, inform choices, reduce risk, streamline operations, and facilitate predictive strategies, thereby improving efficiency and accountability in public procurement practices. The lessons derived from SCM's utilisation of BDA can serve as a guide for driving advancements in sustainable public procurement. Thus, it is empirically understood that the dynamics of BDA are in the context of SPPP.

Big Data Characteristics

The concept of BDA is defined by its fundamental characteristics, which are critical in understanding its application in various domains. Darvazeh, Vanani, and Musolu (2020) define big data as a vast collection exceeding an exabyte, while the basic definition states that it surpasses the capacity of traditional database tools (Chong & Shi, 2015). BDA involves the application of advanced analytics to vast, heterogeneous datasets containing structured, semi-structured, or unstructured data from diverse sources (Rydning & Shirer, 2021; Das, 2020). These attributes enable timely decision-making, predictive modelling, and increased business intelligence.

The architecture-based perspective of BDA emphasises the challenge posed by the rapid creation of data as the global data volume continues to increase exponentially (Rydning & Shirer, 2021). Conversely, the attributive viewpoint defines BDA through its five key attributes: volume, variety, veracity, velocity, and value (Khan et al., 2018). The "5Vs" capture BDA's essence, showcasing its capability to transform raw data into actionable insights for informed decisions. The five generic BD attributes are expanded to ten by adding validity, viscosity, variability, viability, and volatility (Verma, 2017; Khan et al., 2018). This significantly affects SPPP, where accurate insights drive ecologically responsible choices. The expanded 10V characteristics of BDA attributes are critical to Big Data users and managing the inherent challenges with (i) system scalability, (ii) reaction time to user requests, (iii) transaction security, and (vi) the dependability and availability of processing findings (Ezzahra, Nadia & Imane, 2019) in the context of SPPP (Khan et al. (2018).

The first attribute, *volume,* signifies exponential growth in data. In the context of SPPP, this poses a challenge in effectively processing and deriving meaningful insights from massive datasets (Verma, 2017). The value of data generated is pivotal in SPPP, as organisations strive to extract meaningful insights from sustainability-related data (Hussein, 2020). Data *velocity*, or the speed at which data is generated and analysed in real-time, is vital for making informed decisions aligned with dynamic sustainability considerations (Mageto, 2021). *Veracity*, indicating data accuracy and reliability, is crucial in SPPP for maintaining consistent and dependable data sources (Bauhr et al., 2020). While *viscosity,* reflecting resistance to data change, becomes apparent in SPPP while handling diverse and interconnected datasets (Sun et al., 2018). The *variability* of data sources and formats introduces complexity in data integration (Hussein, 2020). On the other hand, *volatility* refers to the duration of data validity, which is particularly pertinent in SPPP due to the ever-changing environmental and social factors (Anuradha, 2015). *Viability* relates to the sustainability and feasibility of using data-driven initiatives to achieve organisational goals, including consideration of ethical implications (Hussein, 2020).

Additionally, *validity* focuses on the reliability of data sources and analyses, which is vital for supplier assessments and environmental impact evaluations in SPPP (Henry & Venkatraman, 2015). Lastly, *variety* encompasses the diverse nature of data sources and formats, requiring effective data management to extract meaningful insights (Verma, 2017). The adoption of BDA presents both challenges and benefits. While these attributes hold transformative potential for SPPP, organisations must effectively manage the complexity introduced by these characteristics to derive actionable insights from extensive datasets. Understanding these ten attributes of BDA is paramount for organisations seeking to leverage data-driven insights while navigating the intricacies inherent in its implementation within the context of SPPP.

Sustainable Public Procurement Practices (SPPP)

SPPP became a vital tool for advancing sustainability amidst the escalation of global human activity towards critical social and ecological thresholds, impacting society's ability to meet its needs. SPPP is positioned as a pivotal contributor to achieving sustainable development, particularly given the increasing scale of government expenditures (Zaidi et al., 2019). However, the current landscape reveals a hybrid approach, wherein only 30% of the larger projects adhere to sustainability policies. A substantial 70% of public expenditure managed by decentralised units needs more sustainable approaches, impeding potential value creation (Vluggen et al., 2019). SPPP's significance lies in its integration of criteria prioritising environmental conservation, economic advancement, and societal considerations (Kozuch et al., 2022; Prier et al., 2016). Beyond economic signals, SPPP drives sustainable practices and technological innovations, recognised as a global strategic driver for innovation and sustainability enhancement across both public and private sectors (OECD, 2023; Prier et al., 2016). The 2030 Agenda for Sustainable Development and its 17 Sustainable Development Goals (SDGs) emphasise the importance of sustainable practices globally (UN, 2015). Numerous international institutions, governments, and private entities have embraced sustainability within procurement criteria, with strategic guidelines developed to assist governments in formulating policies aligned with SPPP (The World Bank, 2019; UN, 2017; African Development Bank, 2020). However, this trend is progressing slowly in developing nations. Key pillars must be considered to evaluate SPP implementation. The OECD's four-pillar benchmark, encompassing legal, regulatory, and policy frameworks, institutional structures, procurement operations, accountability, integrity, and transparency, provides a comprehensive framework that empowers countries to assess their procurement systems and practices (OECD, 2019).

The institutional structures for public procurement exhibit variability across countries, encompassing decentralised and centralised approaches (Arrowsmith & Kunaka, 2018). While centralisation fosters uniformity and consistency, decentralisation allows flexibility (Lu & Ma, 2017). The effectiveness of these structures is influenced by the role of the procurement agency within them, as well as the agency's organisational structure (Treibich, 2018). *A robust legal framework* is essential for supporting sustainable public procurement (Nogues Comas & Mendes Dos Santos, 2021). SPPP requires adequate legal provisions, integration of regulatory instruments, and alignment with developmental goals (Zaidi et al., 2019; African Development Bank, 2020). However, a gap often exists in the legal framework in terms of encompassing economic, environmental, and social factors (Halonen, 2021). *Institutional frameworks and management capacities* are crucial for sustainable procurement; autonomous institutions, efficient regulatory bodies, and robust institutional development all contribute to effective SPPP (The

World Bank, 2019; African Development Bank, 2020; UNEP, 2012; Thai, 2017). Sustainable procurement procedures influence markets, promoting sustainability in production and consumption (Zaidi et al., 2019; African Development Bank, 2020; Roman, 2017; Delmonico et al., 2018). To ensure integrity, accountability, and transparency, SPP requires a supportive legal framework and robust control systems (African Development Bank, 2020; Enweremadu & Ifejika, 2017; Williams & Ehiabhi, 2021). Effective complaints mechanisms, ethical standards, and anti-corruption measures contribute to a transparent and accountable procurement system (OECD, 2016; Gichio, 2014; Sartor & Beamish, 2020). In this context, aligning BDA with SPPP can drive transformative change. BDA's potential to enhance data-driven decision-making, transparency, and efficiency within procurement operations holds promise for revolutionising procurement practices and advancing sustainability goals (Nogues Comas & Mendes Dos Santos, 2021; Chakraborty et al., 2022; Langseth & Haddara, 2021). This area presents an opportunity for future exploration and implementation.

Enhancing Key Procurement Principles with BDA

The key procurement principles, including value for money, economy, integrity, fit for purpose, efficiency, transparency, and fairness, are central to effective and sustainable procurement practices as identified by the World Bank (2019). The key procurement principles encompass foundational guidelines and conceptual frameworks that direct the procedural aspects of procuring goods, services, or works in a manner characterised by equity, transparency, and operational efficiency. This is evident in Morris (2019), who argues that the ability of most developing nations to plan and execute large-scale procurement projects is highly constrained due to non-compliance with these key principles. Hence, the success of these projects is inextricably linked to how the key procurement principles were adopted within the process (Trevino Lozano & Martin-Ortega, 2023). Integrating BDA into the processes offers transformative possibilities for enhancing public procurement (Vluggen et al., 2019; Mélon, 2020). Figure 3 summarises the seven key procurement principles (World Bank, 2019):

Figure 2: Key procurement principles
Source: The World Bank (2019)

Value for money (VFM) principles are enriched through BDA's ability to provide data-driven insights, supporting supplier evaluation, risk assessment, demand forecasting, and informed decision-making (Vluggen et al., 2019). In terms of *economy*, BDA contributes by automating tasks, enabling comprehensive cost analysis, and identifying efficient procurement pathways, aligning with sustainability objectives (Morris, 2019; Gu et al., 2021). BDA's real-time monitoring capabilities also reinforce integrity principles, facilitating the early detection of deviations and supporting corrective actions (Fazekas et al., 2018). *Fit-for-purpose* principles benefit from BDA's data-driven evaluations, ensuring supplier alignment, risk assessment, and timely adjustments (Choi et al., 2018; Mélon, 2020).

Moreover, the *efficiency* principles are bolstered as BDA automates processes, analyses supplier performance, and identifies cost-saving opportunities through demand forecasting (Özkan et al., 2019; Choi et al., 2018). *Transparency* principles are elevated with BDA's ability to monitor data, detect anomalies, and create transparent supplier databases, promoting ethical and fair practices (Fazekas et al., 2018). *Fairness* principles benefit from data-driven supplier evaluations, identifying biases and inequalities while promoting inclusive procurement practices (Gu et al., 2021; Vassakis et al., 2018). Hence, the successful integration of BDA into SPPP requires a diverse set of skills (Mageto, 2021). Proficiency in analysing vast datasets is crucial, along with technical knowledge of procurement processes and regulations (Hussein et al., 2021). Effective communication and collaboration skills are crucial for establishing supplier partnerships and maintaining transparent procurement processes (Bouamrane & Thomson, 2018; Carter & Rogers, 2019). Data analysis skills are also pivotal, enabling professionals to extract meaningful insights, identify trends, and automate processes (Caniëls et al., 2020; Bouamrane & Thomson, 2018). As BDA emerges as a tool to enhance procurement practices, professionals must be equipped to leverage its capabilities, ensuring transparency, accountability, and sustainable development. By harnessing the potential of BDA, public procurement can transcend traditional boundaries and realise its fundamental principles within a rapidly evolving global business landscape.

RESEARCH METHODOLOGY

Research Context

The research philosophy guiding this study adheres to an epistemological perspective, accommodating diverse knowledge dimensions and harmonising with the quantitative approach (Saunders et al., 2019). This approach recognises the multi-dimensional nature of knowledge and focuses on objective measurements (Jakobsen & Worm, 2020; Leedy & Ormrod, 2015). The chosen research design, a descriptive case study, aligns with the study's focus on interrelationships in the context of contemporary phenomena (Dudovskiy, 2018; Creswell & Creswell, 2017). Given the study's aim to explore the strategic value of BDA, the case study approach provides an in-depth illustration of complex concepts (Rashid et al., 2019; Creswell & Creswell, 2017). The sampling strategy employs probability sampling using stratified sampling, ensuring representation from various categories of Namibian public entities (Government Gazette, 2017). The resulting sample size of 270 is determined using a proportionate stratified random sampling method (Charan & Biswas, 2013). This comprehensive methodological framework lays the groundwork for a thorough investigation into the role of BDA in enabling sustainable procurement practices within the Namibian public sector.

Research design

As McCombes (2019) and Dudovskiy (2018) described, the research design served as a foundational framework that outlined this research strategy and addressed relevant questions by setting study parameters. Both definitions emphasise research methods and data collection, which are essential for addressing the research problem. This study employs a descriptive case study approach, aligning with the approaches of Rashid et al. (2019), Dudovskiy (2018), and Creswell and Creswell (2017). This method is fitting for exploring unfamiliar concepts, understanding relationships, and studying contemporary phenomena where control over events is limited. Given the dynamic nature of public procurement, technological factors, and the emerging concept of BDA, this approach comprehensively examines the perceived strategic value of BDA within SPPP. The case study is particularly relevant in the public sectors of developing nations, where the adoption of BDA is complex (Atkinson et al., 2016). The target population of this study comprised 464 procurement employees from the 116 Namibian public entities governed by the 2015 Namibian Procurement Act (Government Gazette, 2017). The study utilised an online Likert-scaled questionnaire through SurveyMonkey to measure BDA's perceived strategic value, BDA adoption, Technological development, and organisational and industrial environment variables. The research then adopted multivariate statistical analysis to identify patterns, relationships, and associations among the study variables.

DISCUSSION OF RESULTS

Reliability and validity

Cronbach's α was utilised to assess the reliability of the measurement scales for the research constructs. Hair, Sarstedt, Hopkins and Kuppelwieser (2016) recommended a threshold of 0.5 for scale reliability. All reliability index values in this study surpassed this threshold, confirming the scales' reliability. Convergent and discriminant validity were examined to establish construct validity. Convergent validity was assessed using average variance extracted and composite reliability, with values exceeding the recommended thresholds of 0.5 and 0.7, as advised by Haji-Othman and Yusuff (2022) and Hair et al. (2016). Table 1 presents the study's reliability and convergent validity values.

Table 1: Constructs reliability and validity

Study construct	Code	Loadings	AVE	CR	α
Technological Development	TD1	0.77	0.68	0.81	0.890
	TD2	0.88			
Organisation conditions and reconfigurations (OCR)	OCR1	0.87	0.78	0.93	0.828
	OCR2	0.92			
	OCR3	0.89			
	OCR4	0.86			
Industry environment (IE)	IE1	0.75	0.57	0.79	0.677
	IE2	0.96			
	IE3	0.50			
Effective Strategic Role (ERV) BDA	PSV1	0.88	0.86	0.94	0.874
	PSV2	0.97			
	PSV3	0.93			
BDA enabled SPPP (BDA)	BDA 1	0.5	0.57	0.80	0.7
	BDA 2	0.88			

The internal consistency is confirmed by calculating Cronbach's alpha to test the instrument's accuracy and reliability. The adequate threshold value for Cronbach's alpha is that it should be > 0.7. In Table 1, the components Technology Development (TD), Organisation Conditions & Reconfiguration (OCR), Industry Environment (IE), Effective Strategic role/value (ERV), and BDA-Sustainable Public Procurement Practices (SPPP) have Cronbach's alpha values of 0.89, 0.828, 0.677, 0.87 and 0.70, respectively, which confirmed the reliability of the survey instrument. The Cronbach's alpha coefficient for the factors with total scale reliability greater than 0.7. It shows that the variables exhibit a correlation with their component grouping and thus they are internally consistent.

Furthermore, Table 1 presents the study's reliability and convergent validity values. Convergent validity is used to measure the level of correlation of multiple indicators of the same construct that are in agreement. The factor loading of the items, composite reliability and the average variance extracted were calculated to determine convergent validity (Hair et al., 2014). The value of AVE and CR ranges from 0 to 1, where a higher value indicates a higher reliability level. AVE is more than or equal to 0.5, confirming convergent validity. Composite reliability (CR) measures a construct's internal consistency, while Average Variance Extracted (AVE) measures its convergent validity. AVE indicates the extent to which variance in a construct is captured by its indicators, while CR shows how well the items in a scale reliably measure a single construct. Acceptable values are generally considered to be CR ≥ 0.70 and $AVE \geq 0.50$.

Composite reliability (CR) is a measure of the internal consistency of a scale. It assesses how well the items in a scale reliably measure a single, underlying construct. To evaluate the reliability of a measurement scale. All the constructs have TD-0.81, OCR-0.93, IE-0.79, ERV-0.94, and BDA-SPPP-0.80 as acceptable values of CR, with a value greater than 0.70 being considered acceptable. It demonstrates the internal consistency of the scale items. Composite reliability is a measure of internal consistency in scale items (Netemeyer et al., 2003). According to Fornell and Larcker (1981), composite reliability is an indicator of the shared variance among the observed variables used as an indicator of a latent construct.

Average Variance Extracted (AVE) is a measure of convergent validity, indicating the extent to which the variance in the items is explained by the latent construct. It represents the average reliability of the individual indicators within a scale. To assess the convergent validity of a construct. It is also used to test for discriminant validity using the Fornell-Larcker criterion. All the constructs have TD-0.68, OCR-0.78, IE-0.57, ERV-0.86, and BDA-SPPP-0.57, which are acceptable values for an AVE greater than 0.50; values higher than this are considered acceptable. AVE is more than or equal to 0.5, confirming convergent validity.

Discriminant Validity

Discriminant validity concerns the ability of a measurement instrument to distinctly differentiate between diverse constructs or factors while remaining unaffected by other variables (Heale & Twycross, 2015). This study assessed this validity by examining inter-construct correlations, where low correlations signify robust discriminant validity due to independent measurements, while high correlations imply inadequate distinction (Hair et al., 2017). The prominent Fornell-Larcker criterion states that squared correlations between constructs should be smaller than the variance each construct explains (Taherdoost et al., 2022). Ensuring construct uniqueness is pivotal, verified through average variance extracted (AVEs) and squared inter-construct correlations (SICs), where AVEs > 0.5 and the square root of AVEs> SICs substantiate discriminant validity. According to Fornell and Larcker

(1981), if AVE is less than 0.5, but composite reliability is higher than 0.6, the convergent validity of the construct is still adequate.

Table 2: Discriminant validity

	TD	OCR	IE	PSV
Organisation Conditions & Reconfiguration (OCR)	**0.89**			
Industry Environment	0.56	**0.56**		
Effective Strategic Role (ESR) BDA	0.66	0.73	**0.55**	
BDA	0.71	0.66	0.51	**0.8**

Table 2 presents the results for CR and AVE, which would be necessary for consideration in CFA. The acceptable values for CR and AVE should be 0.70 and 0.50, respectively (Awang et al., 2015; Hair et al., 2017). The higher the values of CR and AVE, the more reliable and valid the construct being tested. In this study, all constructs satisfactorily fulfilled the requirements since the values of CR and AVE were greater than the recommended values. Specifically, the range value for CR was between 0.79 and 0.94, and the value of AVE for each construct ranged from 0.57 to 0.86. The next step would be to determine the construct correlation by performing discriminant validity analysis. The results in Table 2 above show the values of construct correlations and the square root of the average variance extracted (SQAVE). The discriminant validity is considered to be satisfactorily fulfilled when the value of SQAVE (in bold) is greater than the value of construct correlation as recommended by Hair et al. (2016). Apart from that, the value of construct correlations must be below 0.85. Therefore, this discriminant validity requirement was met satisfactorily before proceeding to test the hypotheses.

Table 2 observations notably reveal that the square roots of AVEs consistently exceed correlations with other latent variables, further affirming discriminant validity within the measurement model. Discriminant validity is the extent to which a measure of a concept is not correlated with measures of different concepts that it should not be related to. It is a type of construct validity that shows a test or scale is unique and distinct from other measures, ensuring that the results are precise and meaningful. This is proven by low or no correlation between tests measuring unrelated constructs, such as a math test and a spelling test.

Confirmatory factor analysis

The assessment of data appropriateness for factor analysis involved using the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity, as shown in Table 3. The result presented in Table 3 shows a KMO value above 0.80, exceeding the recommended threshold of 0.6, as recommended by Taherdoost, Sahibuddin & Jalaliyoon (2022). Likewise, the study's results all yielded significance levels of < 0.001, indicating a strong relationship between the study constructs. Thus, the study conducted an exploratory factor analysis following the results.

Table 3: KMO and Bartlett's Test results

		TD	OCR	IE	PSV	BDA
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.91	0.94	0.84	0.96	0.82
Bartlett's Test of Sphericity	Approx. Chi-Square	3150.885	3856.545	3503.715	4015.362	3631.626
	df	91	95	85	89	93
	Sig.	0.000	0.000	0.000	0.000	0.000

Exploratory Factor Analysis (EFA)

Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) measure confirmed that the study data set has significant correlations, allowing for the performance of Exploratory Factor Analysis (EFA). The KMO test is a measure intended to assess the suitability of data for factor analysis. In other words, it tests the adequacy of the sample size. The test measures sampling adequacy for each variable in the model and for the complete model. The study employed EFA to determine the number of variables influencing the study factors and the correlation between the variables. EFA is a multivariate statistical method summarising data to identify relationships and patterns among research variables (Taherdoost et al., 2022). Furthermore, Hair et al. (2017) suggest that researchers must make several statistical and methodological decisions, including (i) techniques to inspect data, (ii) factor analysis technique, (iii) factor retention methodology, (v) factor rotation technique, and (iv) factor loading decision rule to perform EFA. Next, this study employed principal component analysis to simplify the dataset and enhance its interpretability, while minimising data loss (Jolliffe & Cadima, 2016). Additionally, as Howard (2016) suggested, any variable with a correlation coefficient greater than 0.5 is retained for further analysis. The study employed the oblimin rotation method with Kaiser Normalisation and a factor loading decision rule of accepting any loading above 0.6, as suggested by Hair et al. (2016). Table 4 summarises the EFA outcomes.

Table 4: Exploratory Factor Analysis factor loadings

Technological Development (TD)				**Organisation conditions and reconfigurations (OCR)**				**Industry environment (IE)**			
	Rotated Component Matrix				Rotated Component Matrix				Rotated Component Matrix		
	1	2	3		1	2	3		1	2	3
TD1	0.783	-0.36	0.068	OCR1	0.896	-.211	.148	IE1	0.647	0.108	-0.064
TD2	0.844	-0.342	0.067	OCR2	0.892	-.270	.105	IE2	0.638	0.407	0.61
TD3	0.379	.856	.098	OCR3	0.863	-.333	.186	IE3	0.718	0.662	0.498
TD4	0.494	.934	-.140	OCR4	0.866	-.313	.162	IE4	0.183	0.108	-0.377
TD5	0.286	.180	-.777	OCR5	0.332	.096	-.093	IE5	0.207	0.856	0.098
TD6	0.090	.146	-.813	OCR6	0.469	.019	-.094	IE6	0.188	0.934	-0.14
– **Extraction Method:** Principal Component Analysis – **Rotation Method:** Oblimin with Kaiser Normalisation. – Factor loadings less than 0.6 were disregarded for the Structural Equation Modelling (SEM) – Total variance explained = **56.65%**				– **Extraction Method:** Principal Component Analysis. – Rotation Method: Oblimin with Kaiser Normalisation. – Rotation converged in 9 iterations. – Factor loadings less than 0.6 were disregarded for SEM – Total variance explained = **66.75%**				– **Extraction Method:** Principal Component Analysis. – Rotation Method: Oblimin with Kaiser Normalisation. – Factor loadings less than 0.6 were disregarded for SEM – Total variance explained = **52.45%**			

Perceived/Effective Strategic Role/Value (PSV)			**BDA adoption (BDA)**			
Rotated Component Matrix				Rotated Component Matrix		
1	2	3		1	2	3
0.863	0.234	-0.214	BDA1	0.828	0.22	-0.338
0.885	0.282	-0.195	BDA2	0.696	0.209	-0.495
0.859	0.287	-0.238	BDA3	0.096	0.013	-0.853
0.164	0.127	-0.753	BDA4	-0.112	0.153	-0.903
0.138	0.18	-0.777				
– **Extraction Method:** Principal Component Analysis. – Rotation Method: Oblimin with Kaiser Normalisation. – Rotation converged in 9 iterations. – Factor loadings less than 0.6 were disregarded for SEM – Total variance explained = **57.65%**			– **Extraction Method:** Principal Component Analysis. – Rotation Method: Oblimin with Kaiser Normalisation. – Rotation converged in 9 iterations. – Factor loadings less than 0.6 were disregarded for SEM – Total variance explained = **54.75**%			

All study variables with factor loadings above the prescribed threshold (0.6), as proposed by Hair et al. (2014), in Table 4 and can be used to measure Technological development (TD), Organisation conditions and reconfigurations (OCR), Industry environment (IE), Perceived/Effective Strategic role/value (PSV), and BDA-SPPP adoption (BDA). When the overall variation explained by factor loadings exceeds fifty per cent, the data is deemed credible and free of random errors. *Technological development* (TD) was assessed using ICT infrastructure (TD1) and Scalability (TD2). Factor loadings for TD variables were above the threshold (TD1: 0.87, TD2: 0.94), indicating a relationship. TD positively influenced perceived strategic value (PSV) with a loading of 0.08. Although not strong, it suggests an effect. TD also influenced OCR (0.89) and IE (0.40), indicating a well-connected model. Thus, TD influenced PSV, impacting BDA adoption and SPPP transformation. *Organisational conditions and reconfigurations (OCR) were measured through variables such as* management commitment (OCR1) and staff capabilities (OCR2). All factor loadings exceeded the cut-off (OCR1: 0.93, OCR2: 0.96). OCR influences PSV by 58% (0.58 loading). OCR also impacted TD (0.89) and IE (0.46). *The industry environment (IE) was assessed using variables such as the* legal framework (IE1), risk management (IE3), and business partners' readiness (IE2). IE1, IE2, and IE3 influenced the industry environment by 87%, 98%, and 69%, respectively. IE influenced PSV by 15%. *The* *perceived/effective strategic role/value of BD* (PSV) was measured using Procurement analytics (PSV1), strategic function (PSV2), and Integrations (PSV3). Correlations between PSV and PSV1 (0.9), PSV2 (0.55), and PSV3 (0.97) exceeded the cut-off values. PSV influenced BDA adoption by 82%.

DISCUSSION

The research objective is to establish the strategic and effective role of Big Data Analytics (BDA) in enhancing sustainable public procurement practices (SPPP), aligning with the objectives of the Namibian Procurement Act 2015. The research further seeks to evaluate the factors impacting the technological, organisational and environmental context of public procurement principles through data-driven insights on the view of economic constraints and inequalities. The use of the TOE factors to assess the Namibian government's readiness to adopt BDA in public procurement indicates that Namibia has a well-developed ICT infrastructure and has invested in expanding its broadband network. Initiatives like the Namibian E-GP system promote the use of technology in procurement. This technological development supports BDA's strategic effective role/value, indicating that Namibia is prepared for BDA adoption in public procurement. The readiness of Namibian public procurement organisations to adopt BDA varies, as some organisations are open to embracing new technologies and changes, while others may require more resources or expertise for successful BDA integration. Variables such as management commitment, staff capabilities, procurement structures, and change management influence BDA's strategic effectiveness and value within organisations. Favourable environmental factors, including a commitment to transparency and accountability through initiatives like the Procurement Act, create a conducive legal framework for BDA adoption. However, cultural and social factors, such as resistance to change and traditional procurement preferences, might affect BDA adoption despite the supportive legal environment. BDA's adoption offers significant strategic value, including enhanced decision-making, improved efficiency, increased transparency, and improved supplier performance in procurement. BDA's strategic effective role/value influences its adoption, leading to the transformation of sustainable public procurement practices in Namibia. Namibia's technological readiness and supportive environmental factors make it conducive to adopting BDA in public procurement.

Practical implications

The study's practical implications extend to Namibian public procuring entities and policymakers. Integrating BDA holds several noteworthy implications. Integrating Big Data Analytics (BDA) in public procurement holds diverse implications for public procuring entities and policymakers. BDA's predictive analytics enhances demand forecasting accuracy, minimising understocking and overstocking risks. Its algorithms aid in risk mitigation and fraud detection, bolstering risk management strategies. Budget allocation optimisation is enabled through spending pattern analysis. Supplier diversity is promoted by BDA's scrutiny of demographics and performance. Real-time market intelligence aids agile procurement strategies. Evidence-based policies can be formulated with BDA insights, enhancing regulatory effectiveness. BDA integration has a significant influence on Namibia's public procurement entities, including the Central Procurement Board, the government, and the PPU. By leveraging the factorial data analytics, the TOE context can shape sustainable policies, monitor compliance, enhance stakeholder engagement, allocate resources more efficiently, and foster global collaboration in sustainable procurement practices.

Theoretical implication

The study's findings significantly enhance our understanding of BDA's pivotal role in the realm of SPPP, particularly within the context of developing nations. This is particularly significant due to the imperative of adopting sustainable procurement practices in advancing the SDGs. The research underscores how BDA can serve as a potent enabler for achieving these ambitious goals by revolutionising procurement processes. A key contribution of the study lies in its recognition of the TOE framework as a robust lens through which to comprehend the adoption of BDA in the sustainable procurement landscape. By meticulously examining the interplay between technological advancements, organisational dynamics, and environmental influences, the research provides valuable insights into the complex ecosystem in which BDA integration unfolds. Intricately examining the technological aspects, the study elucidates how factors such as ICT infrastructure, data quality, and system scalability are crucial for BDA integration. By shedding light on these technological prerequisites, the study underscores the transformative potential of BDA for sustainable procurement, thus guiding stakeholders, including procurement professionals, policymakers, and governments.

Implications for Research Method

The goal of this study was to conduct a factor analysis of a questionnaire to identify the primary factors that measure tourist satisfaction. The likelihood of using factor analysis for the data set is explored with the threshold values of determinant score, Kaiser-Meyer-Olkin and Bartlett's test of Sphericity. Based on the results of this study, it can be concluded that factor analysis is a promising approach for extracting significant factors that explain the maximum variability of the group under study. Hospitality, destination attraction, and relaxation are the major factors extracted using principal component analysis and an oblimin orthogonal factor rotation method to measure tourist satisfaction. The application of factor analysis provides valuable insights for decision-makers and policymakers, enabling them to focus on a few manageable factors rather than a large number of parameters. Nevertheless, before making a stronger decision on the TOE factors to promote BDA adoption for sustainable public procurement practices in a country.

Limitations

This research acknowledges certain limitations. The context-specific findings may only partially apply to other settings. The cross-sectional design prevents establishing relationships. Variable response rates might introduce bias. Contextual constraints and resource limitations influenced the data collection process. These limitations prompt careful interpretation of findings and offer avenues for future research improvement.

CONCLUSIONS

In conclusion, this study underscores the transformative impact of BDA on enhancing SPPP in Namibia. BDA offers practical implications spanning predictive analytics for demand forecasting, risk mitigation, optimised budget allocation, supplier diversity, and real-time market intelligence. Policymakers can craft evidence-based regulations, while stakeholders benefit from improved engagement and resource conservation. BDA's accountability mechanisms ensure procurement practices align with organisational objectives. Embracing BDA in Namibia's public procurement landscape presents an opportunity to drive sustainable practices and contribute to broader societal and environmental goals.

Areas of further research

The study sets the stage for exploring the utilisation of BDA to improve sustainability in Namibia's public procurement processes. This research explores the potential impacts of BDA on sustainable procurement practices within the specific context of Namibia. While investigating factors influencing BDA adoption, it also aims to uncover insights applicable to similar developing countries. The study's focus on short-term BDA effects invites consideration of long-term sustainability outcomes. The role of stakeholder engagement in promoting BDA implementation and the impact of data quality challenges are explored. Integration with other technologies, such as AI and blockchain, is explored to enhance the effectiveness of sustainable procurement. This research lays the groundwork for future exploration and identifies opportunities for further investigation.

Disclaimer

The opinions expressed in this article are the authors' own and may not necessarily align with any affiliated agency's official policies or positions.

Conflict of interest

The authors declare no conflict of interest related to the content discussed in this article.

Funding

No external funding or financial support was received for this research or the preparation of this article.

Ethical consideration

The researcher obtained ethical clearance from the KwaZulu-Natal University Ethics Committee (HSSREC/00003003/2021), ensuring the protection of participants, the maintenance of informed consent, confidentiality, research integrity, and compliance with ethical standards and regulations.

REFERENCES

Aday, S., & Aday, M. S. (2020). Impact of COVID-19 on the food supply chain. Food Quality and Safety, 4(4), 167–180.

Adjei-Bamfo, P. E. T. E. R. (2017). Mainstreaming Sustainable Public Procurement in Ghana's Public Sector: The Role of E-Government (Doctoral dissertation, MPhil. Thesis, University of Ghana, Legon).
Adjei-Bamfo, P. E. T. E. R. (2017). Mainstreaming Sustainable Public Procurement in Ghana's Public Sector: The Role of E-Government (Doctoral dissertation, MPhil. Thesis, University of Ghana, Legon).
Adjei-Bamfo, P., Maloreh-Nyamekye, T., & Ahenkan, A. (2019). The role of e-government in sustainable public procurement in developing countries: A systematic literature review. Resources, Conservation and Recycling, 142, 189–203.

African Development Bank. (2020). Sustainable Public Procurement: Guidance Note. Fiduciary Services and Inspection Department. Abidjan: ADB. Retrieved from https://www.afdb.org/sites/default/files/2020/12/18/guidance_note_-_sustainable_public_procurement.pdf

Alsetoohy, O., Ayoun, B., & Abou-Kamar, M. (2021). COVID-19 pandemic is a wake-up call for sustainable local food supply chains: Evidence from green restaurants in the USA: Sustainability, 13(16), 9234.

Anuradha, J. (2015). A brief introduction to Big Data 5Vs characteristics and Hadoop technology. Procedia Computer Science, 48, 319–324.

Arrowsmith, S., & Trepte, P. (2019). Big data and public procurement: A new era? Public Procurement, 19(2), 149–168.

Atkinson, S., Vranopoulos, G., Clarke, N. (2022). Addressing big data variety using an automated approach for data characterisation. Journal of Big Data, 9(1), 1–28.

Awa, H. O., Ukoha, O., & Emecheta, B. C. (2016). Using the TOE theoretical framework to study the adoption of the ERP solution. Cogent Business & Management, 3(1), 1196571.

Awang, Z., Afthanorhan, A., Mohamad, M., & Asri, M. A. M. (2015). An Evaluation of Measurement Models for Medical Tourism Research: The Confirmatory Factor Analysis Approach. International Journal of Tourism Policy, 6(1), 29–45.

Bauhr, M., Czibik, Á., de Fine Licht, J., & Fazekas, M. (2020). Lights on the shadows of public procurement: Transparency as an antidote to corruption. Governance, 33(3), pp.495-523.

Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The Impact of Big Data Analytics and Artificial Intelligence on Green Supply Chain Process Integration and Hospital Environmental Performance. Technological forecasting and social change, 165, 120557.

Biswas, S., & Sen, J. (2017). A proposed architecture for big data-driven supply chain analytics. arXiv preprint arXiv:1705.04958.

Bouamrane, M. M., & Thomson, P. (2018). Big data for social sustainability: A case study of the Scottish Government. Sustainability, 10(4), 954.

Caniëls, M. C., Gelderman, C. J., & Janssen, M. F. (2020). The use of BDA in public procurement: A systematic literature review. Journal of Public Procurement, 20(3), 346-374.

Carter, C. R., & Rogers, D. S. (2019). A framework of sustainable supply chain management: Moving toward a new theory. International Journal of Physical Distribution and Logistics Management, 49(5), 462–488.

Chakraborty, S., Ahmed, M., & Cetindamar, D. (2022). Public Procurement, Big Data Analytics Capabilities, and Healthcare Supply Chain Sustainability. In the Hawaii International Conference on System Sciences.

Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J. L. H., & Baral, M. M. (2022). Blockchain Technology for Supply Chains operating in emerging markets: an empirical examination of the technology-organisation-environment (TOE) framework. Annals of Operations Research, 1-28.

Choi, Y., Lee, H., & Irani, Z. (2018). Big data-driven fuzzy cognitive map for prioritising IT service procurement in the public sector. Annals of Operations Research, 270, 75–104.

Chong, D., & Shi, H. (2015). BDA: a literature review. Journal of Management Analytics, 2(3), 175–201. doi:10.1080/23270012.2015.1082449

Crawford, K., & Schultz, J. (2018). Big data and due process: Toward a framework to redress predictive privacy harms. BCL Rev., 55, 93.

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. Sage Publications.

Darvazeh, S. S., Vanani, I. R., & Musolu, F. M. (2020). BDA and its applications in supply chain management. New Trends in the Use of Artificial Intelligence for the Industry, 4.0, 175.

Das, N., (2020). Big data analytics for medical applications. International Journal of Modern Education and Computer Science, 12(2), 35.

Delmonico, D., Jabbour, C. J. C., Pereira, S. C. F., de Sousa Jabbour, A. B. L., Renwick, D. W. S., & Thomé, A. M. T. (2018). Unveiling barriers to sustainable public procurement in emerging economies: Evidence from a leading sustainable supply chain initiative in Latin America. Resources, Conservation and Recycling, 134, 70–79.

Dudovskiy, J. (2018). The Ultimate Guide to Writing a Dissertation. ResearchMethodology.Net, 1–216. https://research-methodology.net/product/the-ultimate-guideto-writing-a-dissertation-in-business-studies-a-step-by-step-assistance-january-2018- edition/

Enweremadu, D. U., and Ifejika, S. I. (2017). Institutionalising Transparency and Accountability in Nigerian Public Procurement Process. Ibadan Journal of Sociology, 5(1), 73–107. Gichio, D. (2014). Public procurement in Kenya.

Ezzahra, M. F., Nadia, A. F. I., & Imane, H. I. L. A. L. (2019, October). Big Data Dependability Opportunities and Challenges. In 2019 1st International Conference on Smart Systems and Data Science (ICSSD) (pp. 1–4). IEEE.

Farooque, M., Zhang, A., Thürer, M., Qu, T., & Huisingh, D. (2019). Circular supply chain management: A definition and structured literature review. Journal of Cleaner Production, 228, 882–900.

Fazekas, M., Cingolani, L., & Tóth, B. (2018). Innovations in objectively measuring corruption in public procurement. Governance indicators. Approaches, progress, promise, 154–185.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International journal of information management, 35(2), 137–144.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International journal of information management, 35(2), 137–144.

Gichio, D. (2014). Public procurement in Kenya.

Government gazette of the Republic of Namibia (2017).

Grandia, J., & Voncken, D. (2019). Sustainable public procurement: The impact of ability, motivation, and opportunity on the implementation of different types of sustainable public procurement. Sustainability, 11(19), 5215.

Grover, V., Chiang, R. H., Liang, T. P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. Journal of Management Information Systems, 35(2), 388–423.

Gu, Y., Tinn, R., Cheng, H., Lucas, M., Usuyama, N., Liu, X., & Poon, H. (2021). Domain-Specific Language Model Pretraining for Biomedical Natural Language Processing. ACM Transactions on Computing for Healthcare (HEALTH), 3(1), 1–23.

Hair JF, Sarstedt M, Hopkins L, & Kuppelwieser V. (2016). Partial Least Squares Structural Equation Modelling. Sage Publications, Thousand Oaks

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modelling methods. Journal of the Academy of Marketing Science, 45(5), 616-632.

Hair, J., Hult G.T.M., Ringle, C., & Sarstedt, M. (2014). A primer on partial least squares structural equation modelling (PLS-SEM), Sage Publications, Los Angeles, 2014

Haji-Othman, Y., & Yusuff, M. S. S. (2022). Assessing Reliability and Validity of Attitude Construct Using Partial Least Squares Structural Equation Modelling (PLS-SEM). International Journal of Academic Research in Business and Social Sciences, 12(5), 378 – 385.

Halonen, K. M. (2021). Is public procurement fit for reaching sustainability goals? A law and economics approach to green public procurement. Maastricht Journal of European and Comparative Law, 1023263X211016756.

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. Evidence-based nursing, 18(3), 66–67.

Heidari, A. (2018). Exploration of Big Data in Procurement-Benefits and Challenges.

Henry, R., & Venkatraman, S. (2015). Big data analytics is the next big learning opportunity. Journal of Management Information and Decision Sciences, 18(2), 17.

Hopwood, C. J., Bleidorn, W., & Wright, A. G. (2022). Connecting theory to methods in longitudinal research. Perspectives on Psychological Science, 17(3), 884–894.

Hussein, A. A. (2020). Fifty-six big data V's characteristics and proposed strategies to overcome security and privacy challenges (BD2). Journal of Information Security, 11(4), 304–328.

Ibrahim, I., & Binti Jaafar, H. S. (2016). Factors of environmental management practices adoption. Procedia-Social and Behavioural Sciences, 224, 353–359.

Ivanova, S., & Ivanov, O. (2020). Education in the Era of the Fourth Industrial Revolution: Development Vector, Prospects and Challenges for Russia. Space and Culture, India, 7(5), 70–79.

Jakobsen, M., & Worm, V. (2020). The Need for a Phenomenological Perspective in International Business Studies: Different Philosophies of Science and Their Consequences. In Adapting to Environmental Challenges: New Research in Strategy and International Business (pp. 189–213). Emerald Publishing Limited.

Kabanda, G. (2020). An evaluation of big data analytics projects and the project's predictive analytics approach. Oriental Journal of Computer Science and Technology, 12(4), 132–146.

Kamble, S. S., & Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation. International journal of production research, 58(1), 65–86.

Khalid, H., Maroufkhani, P., Tseng, M. L., Iranmanesh, M., & Ismail, W. K. W. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. International journal of information management, 54, 102190.

Khan, N., Alsaqer, M., Shah, H., Badsha, G., Abbasi, A. A., & Salehian, S. (2018). The 10 Vs, Issues and Challenges of Big Data. Proceedings of the 2018 International Conference on Big Data and Education - ICBDE '18. doi:10.1145/3206157.3206166

Kiciński, J., Chaja, P., & Chaja, P. (2021). Industry 4.0—The Fourth Industrial Revolution. Climate Change, Human Impact and Green Energy Transformation, 115-140.

Klingler, D. U., & Schooner, S. L. (2023). Promoting Sustainable Public Procurement through Economic Policy Tools: From Moral Suasion to Nudging. European Journal of Public Procurement Markets, 4(4), 67–79.

Kozanoglu, D., Chakraborty, S., & Murad, M. A. U. (2022). Public Procurement, Big Data Analytics Capabilities, and Healthcare Supply Chain Sustainability.

Kozuch, A. C., von Deimling, C., & Eßig, M. (2022). Implementing green public procurement: A replication study. Journal of Cleaner Production, 377, 134424.

Langseth, M., & Haddara, M. (2021). Exploring data analytics adoption in public procurement: The case of Norway. Å kjøpe for Norge, 223-256.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. Business Horizons, 60(3), 293–303.

Leedy, P. D., & Ormrod, J. E. (2015). Practical research. Planning and design (11th ed.). Boston, MA: Pearson

Lenderink, R. J. (2019). Unsupervised Outlier Detection in Financial Statement Audits (Master's thesis, University of Twente).

Liu, H., Li, X., Wang, W., Zheng, Y., Lv, H., & Lv, Z. (2022). Big data analysis of the internet of things in the digital twins of a smart city based on deep learning. Future Generation Computer Systems, 128, 167–177.

Lu, W. M., & Ma, X. (2017). How institutional structures shape procurement practices in China: Evidence from a survey of county-level governments. Public Administration Review, 77(4), pp.582-592.

Mageto, J. (2021). BDA in Sustainable Supply Chain Management: A Focus on Manufacturing Supply Chains. Sustainability, 13(13), 7101.

Marenga, R. (2020). Analysing the Performance of Public Enterprises in Namibia: A Challenge for the Practice of Public Administration. Journal of Governance and Regulation, 9(3).

Maroufkhani, P., Wan Ismail, W. K., & Ghobakhloo, M. (2020). Big Data Analytics Adoption Model for Small and Medium Enterprises. Journal of Science and Technology Policy Management, 11(4), 483-513.

McCombes, S., & van den Eertwegh, L. (2019). Courses of Nature. Junctions: Graduate Journal of the Humanities, 4(1).

Meehan, J., & Bryde, D. J. (2015). A field-level examination of the adoption of sustainable procurement in the social housing sector. International Journal of Operations & Production Management, 35(7), 982-1004.

Mélon, L. (2020). More than a nudge? Arguments and tools for mandating green public procurement in the EU. Sustainability, 12(3), 988.

Mohungoo, I., Brown, I., & Kabanda, S. (2020). A systematic review of implementation challenges in public E-Procurement. In Responsible Design, Implementation and Use of Information and Communication Technology: 19th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2020, Skukuza, South Africa, April 6–8, 2020, Proceedings, Part II 19 (pp. 46–58). Springer International Publishing.

Moretto, M., Brazzale, D., Castorina, G., & Moser, C. (2017). Abscisic acid is a major regulator of grape berry ripening onset: new insights into ABA signalling network. Frontiers in Plant Science, 8, 1093.

Morris, S. (2019). The Kunming-Vientiane railway: The economic, procurement, labour, and safeguards dimensions of a Chinese Belt and Road project. CGD Policy Paper, 142(7).

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). Scaling procedures: Issues and applications, Sage Publications, Thousand Oaks, CA, 2003.

Nogues Comas, A. A., & Mendes Dos Santos, N. F. (2021). Measuring Public Procurement Rules and Practices. World Bank

OECD (2021), "Reducing administrative burden and simplifying public procurement in Poland", in Better Governance, Planning and Services in Local Self-Governments in Poland, OECD Publishing, Paris. DOI: https://doi.org/10.1787/02aa5682-en

Oruezabala, G., & Rico, J. C. (2012). The impact of sustainable public procurement on supplier management—The case of French public hospitals. Industrial Marketing Management, 41(4), 573–580.

Özkan, E., Azizi, N., & Haass, O. (2021). Leveraging smart contracts in project procurement through DLT to gain sustainable competitive advantages. Sustainability, 13(23), 13380.

Peres, R. S., Rocha, A. D., Leitao, P., & Barata, J. (2018). IDARTS–Towards intelligent data analysis and real-time supervision for Industry 4.0. Computers in industry, 101, 138–146.

Piluso, J., Leimer, M., & Zhang, K. (2016). Empowered by analytics: procurement in 2025. EY: Building a better world, 11(14).

Prier, E., & Schwerin, E., (2016). Implementation of sustainable public procurement practices and policies: A sorting framework. Journal of Public Procurement, 16(3), 312–346.

Prier, E., Schwerin, E., & McCue, C. P. (2016). Implementation of sustainable public procurement practices and policies: A sorting framework. Journal of Public Procurement, 76, 340–351.

Rashid, Y.; Rashid, Ammar; Warraich, Muhammad Akib; Sabir, Sana Sameen; Waseem, Ansar (2019). Case Study Method: A Step-by-Step Guide for Business Researchers. International Journal of Qualitative Methods, (18), 160940691986242–. doi:10.1177/1609406919862424

Rejeb, A., Rejeb, K., Treiblmaier, H., Appolloni, A., Alghamdi, S., Alhasawi, Y., & Iranmanesh, M. (2023). The Internet of Things (IoT) in healthcare: Taking stock and moving forward. Internet of Things, 100721.

Roman, A. V. (2017). Institutionalising sustainability: A structural equation model of sustainable procurement in US public agencies. Journal of Cleaner Production, 143, 1048-1059.

Roos, T., (2016). Kvasir: Scalable provision of semantically relevant web content on big data framework. IEEE Transactions on Big Data, 2(3), 219-233.

Rydning, J., & Shirer, M. (2021). Data Creation and Replication Will Grow at a Faster Rate than Installed Storage Capacity. Minnesota: IDC.

Saeed, M. (2022). Big Data Analytics Adoption in the Indian Insurance Industry: Challenges and Solutions. In Big Data Analytics in the Insurance Market (pp. 81-102). Emerald Publishing Limited.

Saint, J., & Gutierrez, A. (2017). Adoption of learning analytics in the UK: Identification of key factors using the TOE framework.

Sartor, M. A., & Beamish, P. W. (2020). Private sector corruption, public sector corruption and the organisational structure of foreign subsidiaries. Journal of Business Ethics, 167(4), 725-744.

Schwab, K. (2018). The Fourth Industrial Revolution: What It Means, How to Respond. Geneva: World Economic.

Schwerin, E., & Prier, E. (2013). Rent-seeking obstacles to changing environmental practices and sustainable public procurement in China. Environmental Practice, 15(3), 240-252.

Sharma, A. & Pandey, H. (2020). Big Data and Analytics in Industry 4.0. In: Nayyar, A., Kumar, A. (eds) A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development. Advances in Science, Technology & Innovation. Springer, Cham. https://doi.org/10.1007/978-3-030-14544-6_4

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2020). Critical analysis of big data challenges and analytical methods in public sector procurement. International Journal of Information Management, 50, 66–75.

Sönnichsen, S. D., & Clement, J. (2020). Review of Green and Sustainable Public Procurement. Towards circular public procurement. Journal of Cleaner Production, 245, 118901.

Steenkamp, I., & Tekelas, F. (2021). Identify Research Gaps for Future Research.

Stoffel, T., Cravero, C., La Chimia, A., & Quinot, G. (2019). Multidimensionality of sustainable public procurement (SPP)—Exploring concepts and effects in Sub-Saharan Africa and Europe. Sustainability, 11(22), 6352.

Sun, Z., Strang, K., & Li, R. (2018). Big data with ten big characteristics. In Proceedings of the 2nd International Conference on Big Data Research (pp. 56–61).

Taherdoost, H. A. M. E. D., Sahibuddin, S. H. A. M. S. U. L., & Jalaliyoon, N. E. D. A. (2022). Exploratory factor analysis: concepts and theory. Advances in applied and pure mathematics, 27, 375–382.

Thakurta, R., & Guha Deb, S. (2023). Limited Effectiveness of IT/IS Investments in an Emerging Economy: Evidence from India and Implications. ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 54(1), 82–109.

The World Bank. (2019). Procurement guidance: Sustainable procurement (2nd ed.). Washington: The World Bank.

Tornatzky, L.G. & Fleischer, M. (1990). The process of technology innovation. Lexington: Lexington Books.

Treibich, T. (2018). Centralisation and Accountability: Theory and evidence from public procurement. American Political Science Review, 112(4), 1062–1079.

Treviño Lozano, L., & Martín-Ortega, O. (2023). Sustainable public procurement of infrastructure and human rights: linkages and gaps.

Ullah, F., Qayyum, S., & Shahzad, D. (2022). Big data in construction: current applications and future opportunities. Big Data and Cognitive Computing, 6(1), 18.

United Nations. (2020). United Nations E-Government Survey 2020; Digital Government in the Decade of Action for Sustainable Development. New York: United Nations Department of Economic and Social Affairs.

Vassakis, K., Petrakis, E., & Kopanakis, I. (2018). Big data analytics: Applications, prospects and challenges. Mobile big data: A roadmap from models to technologies, 3–20.

Verma, S. (2017). Big Data and Advanced Analytics: Architecture, Techniques, Applications, and Challenges. International Journal of Business Analytics, 4(4), 21–47. doi:10.4018/ijban.2017100102

Vluggen, R., Gelderman, C. J., Semeijn, J., & Van Pelt, M. (2019). Sustainable public procurement—External forces and accountability. Sustainability, 11(20), pp.5696.

Wang, L., Bi, Z., Jin, Y., Maropoulos, P., Zhang, W. J. (2023). Internet of things (IoT) and big data analytics (BDA) for digital manufacturing (DM). International Journal of Production Research, 61(12), 4004–4021.

Williams, O., & Ehiabhi, T. A. F. A. M. E. L. (2021). Transparency and public procurement practices in the Nigerian Civil Service. African Journal of Business Management, 15(1), 41–48.

Zaidi, S. A. H., Mirza, F. M., Hou, F., & Ashraf, R. U. (2019). Addressing sustainable development through sustainable procurement: What factors resist the implementation of sustainable procurement in Pakistan? Socio-Economic Planning Sciences, 68, 100671.

