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LEVERAGING BIG DATA ANALYTICS TO ENHANCE SUSTAINABLE PUBLIC PROCUREMENT PRACTICES IN NAMIBIA

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ABSTRACT

Data-driven public procurement practices are earmarked to improve quality monitoring and compliance, as well as real-time tracking for transparency and accountability. The research objective is to examine the strategic role of Big Data Analytics (BDA) in enhancing sustainable public procurement practices (SPPP) that align with the objectives of the Namibian Procurement Act, 2015. The research further establishes potential improvements to key procurement principles through data-driven insights, amid a constrained technology-organisation-environment ecosystem and uncertainty from an information-processing lens. This quantitative research design, rooted in a deductive positivist perspective, focuses on epistemological assessment of BDA impact within the Technology-Organisation-Environment (TOE) framework. The research design employs a descriptive case study, enabling the exploration of cause-and-effect relationships and an information-processing lens. Diverse perspectives are integrated via stratified sampling, resulting in a sample size of 270. The study employs inferential and multivariate statistical analysis to establish the effective strategic value and efficiency of sustainable public procurement practices following the enactment of the Public Procurement Act, 2015. The findings highlighted hindrances, including leadership commitment, procurement capacity, procedural complexities, and resource constraints, that impede the shift towards sustainable public procurement. These findings culminate in a TOE framework-rooted structural model equation within the lens of information processing theory. This research provides policymakers, public procurement professionals, and technology providers with practical insights to enhance the strategic value of BDA for sustainable procurement.

KEYWORDS: Technology-Organisation-Environment factors, big data analytics, information processing, sustainable public procurement practices.

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1. INTRODUCTION

The paradigms of sustainable public procurement and transformative public procurement capacity aim to integrate environmental, social, and economic considerations within the framework of innovative public procurement practices. The ecological and innovative confluence 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 corollary challenge of graft and mismanagement within procurement contexts requires strategic functions, as well as efficient and effective sustainable public procurement, to contribute to the achievement of the Sustainable Development Goals of ending poverty and promoting shared prosperity. This study presents the underpinning theoretical framework, a key literature review that encapsulates the background and research problem, the research methodology, and a thorough discussion of the results. Distinctively, the research focuses on the nexus of BDA and sustainable procurement within the specific context of Namibia, a developing nation. Through this focused aperture, the study is poised to deliver pragmatic insights that resonate both within the academic discourse and practical policy landscapes.

Background and Research Problem

In parallel, the paucity of sustainable public procurement practices undermines the full potential of procurement as a transformative tool. This transformative endeavour necessitates an interdisciplinary approach, bridging the chasm between sustainability imperatives and procurement practices (Piluso et al., 2016). Amidst the maelstrom of technological upheaval, the recalibration of procurement functions is inexorable (Rejeb et al., 2018). Yet, the comprehensive integration of these transformative digital technologies within procurement paradigms is far from complete (Lenderink et al., 2022). The drivers and motivations for sustainable public procurement (SPP) stem from a growing recognition of the interconnectedness between public procurement decisions and broader sustainability challenges society faces (Wachs et al., 2021), while the evolving digital milieu infuses the emergence of big data analytics (BDA) as a pivotal role in leveraging the deluge of real-time and diverse data streams - trends, patterns, and correlations—bestowing insights that enrich informed decision-making (Schwab, 2018). In the context of the foreground scenario, public procurement, epitomised by its principles of transparency, integrity, competitiveness, and efficiency (Government Gazette, 2017), stands poised to gain significantly from BDA's prowess, TOE framework, and IPT lens. Nevertheless, the integration of BDA within public procurement domains remains constrained, hindered by a multitude of factors (Hopwood, 2019), including data dispersion challenges that Namibia grapples with (Marenga, 2020). Given the complexity and interplay of sustainability imperatives, technological potentials, and procurement exigencies, this study undertakes a comprehensive examination of the role of BDA in promoting sustainable public procurement practices. By leveraging the power of data and analytics, organisations and policymakers can address complex challenges, unlock new opportunities, and create positive societal impact for sustainable public procurement practices. The study's entry point into this discourse is through a transdisciplinary prism—a vantage that seeks to unravel the intricate symbiosis between technological propensities and the contours of sustainable procurement. The research objective is to examine the effective strategic 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 establishes potential improvement on key procurement principles through data-driven insights, amid a constrained technology-organisation-environment ecosystem and uncertainty from an information-processing lens. The research study contemplates groundbreaking insight on how efficient sustainable public procurement can improve the quality of public service delivery through several supply chain channels, such as the selection of higher-quality goods, collaborative data-driven procurement, more reliable and timely delivery of goods, completion of sustainably resilient public infrastructure, and better synchronised planning of electronic purchases and flexible and agile stock management systems.

2. LITERATURE REVIEW

The realm of public procurement faces new challenges and opportunities from global interconnectedness, sustainability, and rapid advancements in data and technology. The intricate web of TOE factors influencing the perceived strategic value of big data analytics (BDA) in the context of sustainable public procurement practices (SPPP) in Namibia involves a dynamic interplay among data, capacity, cognition, and sustainability. Although the study's foundational framework is grounded in the Technology-Organisation-Environment (TOE) framework, the information processing theory entrenches a comprehensive lens through which the strategic value of BDA and its role in enabling sustainable public procurement practices can be analysed. The majority of the literature has focused on innovation and technology in public procurement (Kundu et al., 2020; Eikelboom et al., 2018; Obwegeser & Müller, 2018). Very few studies have focused on what happens to the vast amount of data created in public procurement operations and how it can be utilised to drive sustainability.

3. Theoretical Framework

The dynamic interplay between BDA and information processing theory (IPC) within the framework of TOE. The TOE framework by Tornatzky and Fleischer (1990) explores generic factors to explain and envisage the probability of innovation acceptance (Awa, Ukoha, & Emecheta, 2016). The framework suggests that technological innovations and implementation processes influence three main factors: technological factors, organisational factors, and environmental factors (Oliveira & Martins, 2011). Technological factors analyse the existing internal technologies and the external pool of available technologies relevant to the entity (Ahmad, Janczewski, & Beltran, 2015). The organisational factor refers to the entity's multiple characteristics that form the formal and informal linking structures (Oliveira & Martins, 2011). The environmental factor implies that the adoption of new technology profoundly influences the environment in which the entity operates (Ahmad et al., 2015). When integrated with sustainable public procurement practices, it can improve transparency and accountability, which in turn enables BDA to fortify procurement processes against discretionary procurement activities (Discretion through a formula: Corruption = Monopoly + Discretion - Accountability). Information processing theory (IPT) (Gu et al., 2021) proposes that changes in cognitive procurement functioning occur through the combination of improvements in basic supply chain capacities, sustainable data-driven procurement strategies, and supply chain content knowledge (Herold et al., 2023), to reduce discretion, increase accountability, and increase transparency.

BDA-empowered information processing lens focuses on the precision, analytics and data-driven processes that produce cognitive public procurement practices for sustainable development (including information encoding, speed of organising and processing, and strategic generating outcomes of information operation). BDA examines vast and complex datasets to reveal hidden patterns and insights that extend beyond conventional analysis, improving organisations' strategic decision-making (Lamba et al., 2019; Raut et al., 2021). Information-processing theory is incorporated into the connectionist network model, which compresses redundant information while preserving and differentiating information that predicts reinforcement (Sanda et al., 2024). Transparency and Accountability (TA) in procurement processes is defined as the combination of openness, allowing stakeholders to access and understand procurement information (transparency), and the obligation of entities to justify and be answerable for their decisions (accountability) (Singh & Chan, 2022; Aristotelis et al., 2024). It also includes instituting measures such as audits to ensure fairness, combat corruption, and enhance quality, which are key to promoting ethical practices, maintaining effective governance, reducing corruption, ensuring competition and achieving procurement value (Atkinson, 2022; Kohler & Wright, 2020). In the procurement and BDA domains, IPT explains how organisations manage uncertainty and enhance decision-making through effective data analysis (Nasser, Kamran, & Salam, 2024). BDA is crucial, as it enhances information processing capacity and provides a strategic edge in procurement (Li et al., 2021; Lu et al., 2023). The literature also highlights IPT's role in supply chain management, particularly how BDA enhances transparency, accountability, and efficiency in procurement, as well as combating corruption (Li et al., 2021; Lu et al., 2023; Niu et al., 2021). This study integrates sustainable public procurement, BDA, and TOE within the IPT lens to streamline interactions, where TOE captures strategic data, SPP ensures data integrity and cognitive development, and BDA enhances analytical capabilities, collectively bolstering TA in institutions and SPPP networks.

3.1. Nature of Public Procurement

Sustainable public procurement enriches the traditional value-for-money perspective by adding social, economic, and environmental dimensions, placing equal emphasis on all three (Sanda et al., 2024). Along with them, sustainable procurement practices encompass the essential ingredients of sound public procurement: transparency, fairness, non-discrimination, competitiveness, accountability, and the efficient use of public funds (Aristotelis et al., 2024). E-procurement is divided into e-procurement coordination (EPC) and e-procurement transactional (EPT) applications. EPC enhances operations and supplier relations, whereas EPT improves efficiency in the face of adoption challenges (Singh & Chan, 2022). In this study, e-procurement, encompassing both EPC and EPT, is conceptualised as a strategic asset integral to the modern procurement ecosystem and foundational for integrating advanced technologies such as BDA. Transparency and Accountability (TA) in procurement processes is defined as the combination of openness, allowing stakeholders to access and understand procurement information (transparency), and the obligation of entities to justify and be answerable for their decisions (accountability) (Singh & Chan, 2022; Aristotelis et al., 2024). It also includes instituting measures such as audits to ensure fairness, combat corruption, and enhance quality, which are key to promoting ethical practices, maintaining effective governance, reducing corruption, ensuring competition and achieving procurement value (Atkinson, 2022; Kohler & Wright, 2020). Public procurement data analytics refers to the application of data analysis techniques to extract key insights into the performance of procurement processes, contribute to the policy debate, identify patterns or risks of corruption, detect opportunities to improve the efficiency and effectiveness of procurement processes and analyse the impact of public procurement (World Bank, 2022; Ansari et al., 2022). This seeks to leverage open public procurement data to contribute to the fulfilment of the principles of good public procurement, such as transparency, competition, accountability, efficiency, effectiveness, responsibility, and sustainability (Fazekas et al., 2020).

Procurement analytics, which combines the application of data analysis techniques and the use of public procurement records, reveals that these data can serve as a basis for analysing aspects related to the integrity, efficiency, and competence of procurement processes (Ansari et al., 2022).

3.2. Sustainable Public Procurement

Sustainable Public Procurement (SPP) refers to the practice of integrating environmental, social, and economic considerations into public procurement beyond traditional cost-efficiency and quality criteria and considering the broader impact of procurement decisions on society, the environment, and the economy (Cheng et al., 2018). The drivers and motivations for Sustainable Public Procurement (SPP) stem from a growing recognition of the interconnectedness between public procurement decisions and broader sustainability challenges society faces. Firstly, SPP addresses environmental concerns in public procurement to mitigate the impact of climate change. Thus, governments and public organisations are embracing sustainable procurement by promoting environmentally friendly practices related to curbing carbon emissions and conserving natural resources by aligning purchasing power with environmentally responsible suppliers and products, contributing to global climate change combat (Klingler & Schooner, 2023; van Berkel & Schotanus, 2021; Cheng, 2018; OECD, 2017).

Secondly, as public procurement involves vast supply chains and significant economic influence, there is a growing awareness of the social implications of procurement decisions. Consequently, governments' procurement legislation has included social considerations in contracting processes, including Namibia. SPP seeks to promote fair labour practices, uphold workers' rights, and support social equity and inclusion in supply chains (Siwandeti et al., 2023). By prioritising suppliers that adhere to social factors, public organisations are pivotal in driving positive social change, ensuring that procurement activities have a positive impact on the lives of workers and communities (Bernal et al., 2019; Stoffel et al., 2019). Thirdly, economic factors further bolster SPP. Contrary to the perception that sustainable procurement might be cost-prohibitive, evidence suggests that adopting sustainable practices can lead to long-term economic benefits (Siwandeti et al., 2023; Klingler & Schooner, 2023; Bernal et al., 2019). By considering life cycle costs and the total cost of ownership, public organisations can identify opportunities for cost savings and increased efficiency.

SPP represents a paramount paradigm for envisioning the future, emphasising the imperative of satisfying present needs while safeguarding the capacity of future generations to fulfil their own requirements. Thus, by supporting businesses and industries that prioritise sustainability, the SPP concept harmonises economic, social, and environmental considerations to cultivate a society that is resilient and mutually beneficial. (OECD, 2017).

The multifaceted drivers and motivations for SPP directly influence the perceived value of Big Data

Analytics (BDA) as sustainable procurement practices increasingly take priority (Klingler & Schooner, 2023; Stooffel et al., 2019). Thus, adopting BDA as a strategic approach enhances the effectiveness and impact of SPP initiatives, the perceived strategic value of BDA, and its impact on the adoption of sustainable public procurement for effective decision-making and policy development.

3.3. Description of Big Data Analytics (BDA)

BDA refers to the process of collecting, processing, and analysing large and complex datasets, commonly known as big data, to extract valuable insights and patterns that aid in decision-making, problem-solving, and strategic planning (Rydning & Shirer, 2021). There are two critical elements shaping how Big Data Analytics (BDA) is defined. Firstly, BDA is defined from an architectural perspective. In 2020, 64.2 zettabytes of data were created or duplicated globally, and this number is rising exponentially in relation to installed storage capacity (Rydning & Shirer, 2021). Furthermore, the World Economic Forum (2019) estimated that the world would create 170 zettabytes of data by 2025. From a conservative standpoint, storing and analysing this massive data requires advanced architectural infrastructure (Desjardins, 2019). Hence, BDA definitions highlight that increased data generated presents a challenge for traditional architectures and infrastructures to process massive data in a reasonable amount of time and with an acceptable number of resources. Therefore, modern algorithms and artificial intelligence technologies enable unprecedented levels of detailed information capturing, storing and analytics (Scwab, 2016).

On the other hand, BDA is defined from an attributive perspective, as research-reviewed definitions of big data analytics have identified four significant features essential for defining big data analytics (Ardagna et al., 2016; De Mauro et al., 2016; Ylijoki & Porras, 2016; Isitor & Stanier, 2016). For example, Villars et al. (2011, p.1) defined BDA as "a new generation of technologies and architectures, designed to economically extract value from gigantic volumes of a wide variety of data by enabling high-velocity capture, discovery, and analysis". The BDA definition outlines five notable attributes of BDA: volume (in Terabytes), variety (Structured, semi-structured, and unstructured), veracity (Credibility), velocity (Real-time), and value (economic benefits) (Mageto, 2021; Hu et al., 2014; Villars et al., 2011). Consequently, the "5Vs" have been widely used to define the attributive character of BDA. Verma (2017) added three more: validity (Accuracy), variability (inconsistencies and reliability), and volatility (availability and lifespan). The expanded 8Vs that characterise BDA present challenges in an already technologically constrained public procurement sphere (Verma, 2017). Big Data users face challenges with (i) system scalability, (ii) reaction time to user requests, (iii) transaction security, and (iv) the dependability and availability of processing findings (Ezzahra et al., 2019). These challenges are manifestations of the attributes of Big Data. Thus, BDA adoption requires specialised infrastructure and analytical expertise, as well as BDA's perceived value in public procurement (Chakraborty et al., 2022).

3.4. Leveraging Big Data Analytics for Sustainable Public Procurement

As governments and public organisations increasingly recognise the pivotal role in promoting sustainable development, the perceived value of BDA becomes even more pronounced. Government operations and interactions with ordinary citizens generate massive amounts of data (Androutsopoulou et al., 2019). Thus, BDA adoption requires specialised infrastructure and analytical expertise to advance BDA's perceived value in public procurement (Chakraborty et al., 2022). Leveraging BDA as a powerful tool in sustainable public procurement practices aligns with the broader societal and environmental goals of SPP. Stoffel et al. (2023) assert that by making data-driven decisions, public entities can achieve positive and lasting impacts on the present and future generations, fostering a more sustainable and resilient procurement ecosystem.

BDA enables public entities to identify environmentally friendly suppliers, assess carbon footprints, and optimise resource consumption. This ability to harness data for sustainable decision-making enhances the perceived value of BDA, as it empowers organisations to make informed choices that align with environmental objectives. BDA further helps identify suppliers adhering to ethical labour practices, fair wages, and safe working conditions. This transparency enables public organisations to foster partnerships with socially responsible suppliers, thereby supporting social equity and inclusivity. The perceived value of BDA in this context lies in its ability to mitigate social risks in the supply chain and ensure that procurement practices have a positive impact on workers and local communities. Lastly, BDA facilitates economic efficiency in SPP, aligning with the motivation to achieve cost-effectiveness. By analysing supplier performance, market trends, and pricing data, BDA allows public organisations to optimise procurement processes, identify cost-saving opportunities, and enhance value for money (Klingler & Schooner, 2023). BDA's perceived economic value lies in its potential to generate substantial savings while supporting sustainable businesses and industries, ultimately contributing to broader economic development goals.

3.5. Research Hypotheses Development

The research objective is to examine the effective strategic 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 establishes potential improvements to key procurement principles through data-driven insights, amid a constrained technology-organisation-environment ecosystem and uncertainty from an information-processing lens. The information processing theory brings relevance to exploring the influence of Namibian TOE factors on the perceived strategic value of BDA and its relationship with the adoption of sustainable public procurement practices.

Study hypotheses were formulated to establish the relationship between BDA's perceived strategic value, T-O-E Factors and adoption of SPPP. Each T-O-E framework factor was tested to confirm the factors that influence BDA's perceived strategic value. H4 tested the influence of BDA's perceived strategic value of SPPP adoption.

Table 1: Four Hypotheses SE Testing.

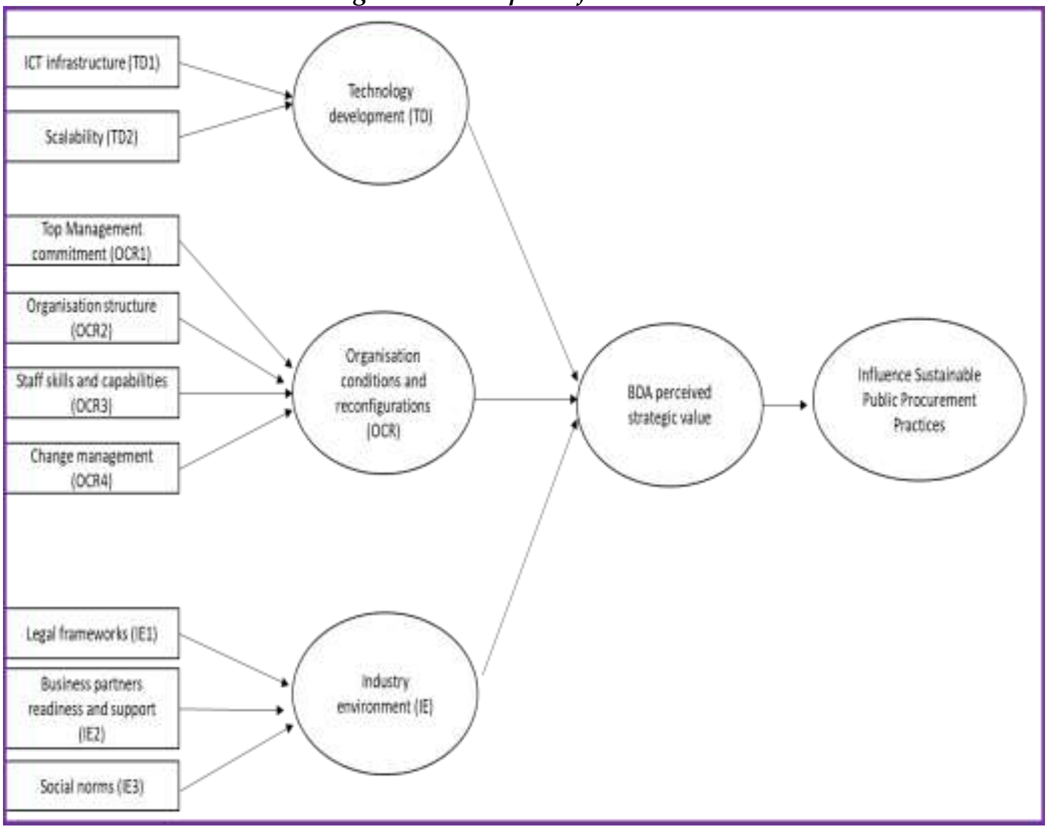
Constructs from the Research Objectives	Hypotheses Development
Influence of Technological Development on BDA's Perceived Strategic Value:	**H1:** Technological development positively influences the BDA's perceived strategic value.
Technological advancements have transformed the way organisations operate and manage data. Research suggests that technological development impacts BDA adoption (Maroufkhani et al., 2023; Chaurasia & Verma, 2020; Verma & Bhattacharyya, 2017). Chen et al. (2015) assert that the availability of advanced data collection and analysis tools enhances the effectiveness and efficiency of sustainable public procurement processes. Therefore, organisations that adopt advanced technological solutions are more likely to perceive BDA as strategically valuable for sustainable procurement practices. While the literature has established the impact of technology on BDA, limited studies have focused on sustainable public procurement and the perceptions and attitudes of BDA users (e.g., decision-makers, analysts) towards these technological advancements and the perceived value.	
Influence of Organisation Conditions and Reconfigurations on BDA's Perceived Strategic Value:	H2: Organisation conditions and reconfigurations positively influence the BDA's perceived strategic value.
The organisational context plays a crucial role in shaping the perceived strategic value of BDA. Organisational factors such as leadership support, organisational culture, and resource allocation impact the adoption and utilisation of BDA in sustainable public procurement (Verma & Bhattacharyya, 2017). Studies (Chatterjee et al., 2022; Batistič & van der Laken, 2019; Chen *et al.*, 2015) have highlighted those organisations with supportive leadership, a culture of data-driven decision-making, and adequate resources are more likely to perceive BDA as strategically valuable	
Influence of Industry Environment Factors on BDA's Perceived Strategic Value:	**H3:** The industry environment positively influences the BDA perceived strategic values.
The industry environment, including regulatory frameworks, market competition, and stakeholders' expectations, can influence the perceived strategic value of BDA in sustainable public procurement. Klingler and Schooner (2023) suggest that organisations operating in industries with a high emphasis on sustainability and transparency are more inclined to value the transparency and accountability BDA enables in the procurement process. Moreover, regulatory requirements promoting data-driven decision-making in procurement processes increase sustainable practices.	
Influence of BDA's Perceived Strategic Value on Sustainable Public Procurement Practices Adoption	**H4:** BDA perceived strategic values positively influence SPPP adoption.
The perceived strategic value of BDA has a significant impact on the adoption of sustainable public procurement practices. Studies have indicated that organisations that perceive BDA as strategically valuable are more likely to adopt and integrate BDA into their procurement processes. The perceived value of BDA is often associated with improved decision-making, enhanced efficiency, cost savings, and better sustainability outcomes.	

Source: Designed by Researchers

The TOE framework is used to construct the conceptual study framework below, which maps out the study constructs and envisaged relationships between the research variables.

The diagrams below depict the conceptual research framework and the associated hypothesis.

Figure 1: Conceptual framework.



Source: Designed by Researcher.

Table 1 below defines the conceptual framework variables related to BDA, SPPP, and the research hypothesis.

4.RESEARCH METHODOLOGY

4.1. Research Design

The research methodology examines the role of BDA in SPPP within the Namibian context, highlighting the crucial significance of its structured approach to conducting research, which encompasses data collection, analysis, and interpretation processes (Creswell & Creswell, 2018; O'Hanlon, 2018). The research paradigm chosen for this study aligns with the quantitative method approach and elements (Saunders et al., 2019). The positivist aspect involves empirical observation and quantification to explore the impact of BDA on SPPP (O'Hanlon, 2018). This approach ensures a comprehensive and robust exploration of the research variables, enriching the study's depth and breadth. The research philosophy guiding this study adheres to an epistemological perspective, accommodating diverse knowledge dimensions and harmonising with the quantitative method approach (Saunders et al., 2019; Jakobsen & Worm, 2020). The descriptive case study design aligns with the study's focus on cause-and-effect relationships in the context of contemporary phenomena (Dudovskiy, 2018; Creswell & Creswell, 2017), as well as its interrogation of BDA's strategic value, providing an in-depth illustration of complex concepts (Rashid et al., 2019; Creswell & Creswell, 2017).

The study's sampling strategies are grounded in probability sampling, utilising stratified sampling, to ensure representation from various categories of Namibian public entities (Government Gazette, 2017). The resulting sample size of 270 was 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 public procurement practices within the Namibian public sector. 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.

4.2. Reliability and Validity

Cronbach's alpha (α) was used in this study to determine the internal consistency of the constructs. According to Hair et al. (2016), a high alpha coefficient indicates that the constructs have a high internal consistency. Although Cronbach's alpha is widely used in studies, Hair et al. (2016) argue that it is a basic reliability test that assumes all items are equally reliable and have equal factor loadings. Unlike Cronbach's alpha, composite reliability considers various factor loadings and is used in structural modelling research to assess reliability and validity as suggested by Haji-Othman and Yusuff (2022). Consequently, this study combines Cronbach's alpha and composite reliability because it prioritises the items based on their reliability. Hair et al. (2016) suggest that a composite reliability value between 0.60 and 0.70 is acceptable, while a value below 0.60 indicates internal inconsistency. An Alpha coefficient between 0.80 < and 0.90 should be regarded as excellent, and anything > 0.90 should prompt the researcher to consider shortening the scale (Bachir, 2017). The study constructs Cronbach's reliability statistics are shown in Table 4-8 below.

Table 1: Reliability and validity statistics.

	Cronbach's Alpha	Composite reliabilities	N of Items
Technology development (TD)	0.890	0.892	2
Organisation conditions and reconfigurations (OCR)	0.828	0.835	4
Industry environment (IE)	0.677	0.685	3
Perceived Strategic Value (PSV)	0.874	0.899	3
BDA adoption (BDA)	0.832	0.845	2

Source: Designed by Researchers.

[Technology Development (TD), Organisation Conditions & Reconfiguration (OCR), Industry Environment (IE), Effective Strategic role/value (ERV), and BDA-Sustainable Public Procurement Practices (SPPP)]

Table 2 shows that the study constructs attained acceptable reliability. Hair et al. (2017) argue that an alpha above 0.90 is risky because it implies an analysis of identical factors, rendering the construct's reliability invalid. Thus, the constructs were further subjected to discriminant validity.

4.3. Discriminant Validity

Discriminant validity is a statistical concept that refers to a measurement instrument's ability to distinguish between different constructs or factors without being influenced by other constructs or factors (Heale & Twycross, 2015). The study assessed discriminant validity by comparing the correlations between the measured constructs or factors. If the correlations are low, it indicates that the constructs or factors are being measured independently and that the instrument has good discriminant validity. On the other hand, if the correlations are high, the instrument cannot distinguish between the constructs or factors and has poor discriminant validity (Hair et al., 2017). Henseler et al. (2015) suggest that the Fornell-Larcker criterion is the dominant approach for assessing discriminant validity in variance-based structural equation modelling. The Fornell-Larcker criterion states that the measured squared correlations between the constructs or factors should be less than the variance explained by each construct or element in the model (Henseler et al., 2015). In other words, the squared correlations should be less than the R2 values for each construct or factor. Discriminant validity is crucial in research to ensure that each construct measures a distinct concept. This is assessed using average variance extracted (AVEs) and squared inter-construct correlations (SICs), with AVEs above 0.5 and the square root of AVE larger than SICs being desirable for achieving discriminant validity. Table 3 illustrates the study variables, AVEs, and SIC.

Table 3: AVEs) and SICs Discriminant validity.

	TD	OCR	IE	PSV
OCR	**0.89**			

IE	0.56	**0.56**		
PSV	0.66	0.73	**0.55**	
BDA	0.71	0.66	0.51	**0.8**

Source: Designed by Researchers

Taherdoost (2016) states that the AVEs represent the proportion of variance in a construct captured by its measures after accounting for measurement error. On the other hand, SICs measure the similarity between different units or items within the same construct. Table 3 illustrates the study findings on AVEs and SICs, which satisfied the circumstances for discriminant validity. The study variables' AVEs and SICs are all above 0.5 and are therefore deemed fit to develop a structural model to validate the acclaimed hypotheses, as suggested by Hair et al. (2017) and Taherdoost (2016).

4.4. Factor Analysis

The primary goal of factor analysis is to identify the number and nature of underlying variables that explain the variation and correlations among indicators (Brown, 2015). This study has five constructs: technology development, organisation conditions and reconfigurations, industry environment, perceived strategic value and BDA adoption. Table 4 summarises the number of variables and corresponding indicators. Burton and Mazerolle (2011) suggest that the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test must be conducted to examine data and sample adequacy before extracting study constructs. Data and sampling adequacy inform the researcher regarding the grouping of survey constructs. As Shrestha (2021) suggested, KMO and Bartlett's sphericity tests are crucial in determining the appropriateness of the data for conducting exploratory factor analysis. The study employed KMO to assess sampling adequacy and Bartlett's test of sphericity to evaluate the strength of relationships among variables (Hadi et al., 2016). The range of KMO statistics is between 0 (indicating extreme sample inadequacy) and 1 (indicating absolute sample adequacy). A statistic of 0.6 is sufficient for measuring adequacy (Shrestha, 2021; Howard, 2016). In comparison, significance levels of < 0.05 for Bartlett's test of sphericity are acceptable, and the relationship between the study variables is regarded as vital (Howard, 2016). Table 4 shows the KMO and Bartlett's Test results to establish whether exploratory factor analysis is viable.

Table 4: Study variables 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

Source: Designed by the Researchers.

The outcomes indicated that TD (0.91), OCR (0.94), IE (0.84), PSV (0.96), and BDA (0.82) all scored above the required 0.6, demonstrating that the data sample is adequate for carrying out EFA. 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.

4.5. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is a multivariate statistical method summarising data to identify relationships and patterns among research variables (Yong & Pearce, 2013). The methodology reorganises the study variables into confined clusters based on their shared variances (Thomas & Brad, 2014). Data is thus cleaned without manipulations. EFA was used to determine the number of variables influencing the study factors and the correlation between the variables, as recommended by Watkins (2018). Moreso, at least three measured variables are required to identify factor loadings (Child, 2006; Fabrigar & Wegener, 2012; Izquierdo et al., 2014). Furthermore, Howard (2016, p.52) suggests that researchers have to 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. Hence, Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) test are used to examine whether the study data set has significant correlations 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. (2014).

Table 5: Exploratory Factor Analysis factor loadings.

Technological Development (TD)	Rotated Component Matrix		
	1	2	3
TD1	0.783	-0.36	0.068
TD2	0.844	-0.342	0.067
TD3	0.379	.856	.098
TD4	0.494	.934	-.140
TD5	0.286	.180	-.777
TD6	0.090	.146	-.813
– **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%			

Organisation conditions and reconfigurations (OCR)	Rotated Component Matrix		
	1	2	3
OCR1	0.896	-.211	.148
OCR2	0.892	-.270	.105
OCR3	0.863	-.333	.186
OCR4	0.866	-.313	.162
OCR5	0.332	.096	-.093
OCR6	0.469	.019	-.094
– **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%			

Industry environment (IE)	Rotated Component Matrix		
	1	2	3
IE1	0.647	0.108	-0.064
IE2	0.638	0.407	0.61
IE3	0.718	0.662	0.498
IE4	0.183	0.108	-0.377
IE5	0.207	0.856	0.098
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 SEM – Total variance explained = 52.45%			

Perceived Strategic Value (PSV) Rotated Component Matrix 1	2	3
0.863	0.234	-0.214
0.885	0.282	-0.195
0.859	0.287	-0.238
0.164	0.127	-0.753
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%		

BDA adoption (BDA)	Rotated Component Matrix		
	1	2	3
BDA1	0.828	0.22	-0.338
BDA2	0.696	0.209	-0.495
BDA3	0.096	0.013	-0.853
BDA4	-0.112	0.153	-0.903
– 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%			

Source: Designed by Researchers.

All study variables with factor loadings above the prescribed threshold (0.6), as proposed by Hair et al. (2014), are considered to measure Technological development (TD), Organisation conditions and reconfigurations (OCR), Industry environment (IE), Perceived Strategic value (PSV), and BDA adoption (BDA).

When the overall variation explained by factor loadings exceeds fifty per cent, the data is deemed credible and free of random errors. In addition, the study did not include any of the highlighted study variables for structural equation modelling because they were discarded for further investigation. Included were TD3 (0.379), TD4 (0.0.494), TD5 (0.286), TD6 (0.090), OCR5 (0.332), OCR6 (0.469), IE4 (0.183), IE5 (0.207), IE6 (0.188), PSV4 (0.164), PSV5 (0.138), BDA3 (0.096), and BDA4 (-0.112) as shown in Table 5.

4.6. Factor Communalities

Factor communalities quantify the fraction of variation explained by the factor model. Eaton et al. (2019) suggest that communalities with values < 0.5 are unacceptable and should be considered cut-off values. Communalities values > 0.7 are ideal and should be retained for further analysis. Table 6 shows the communalities using the Principal Component Analysis Extraction Method.

Table 6: Communalities.

Technological Development			**Organisation conditions and reconfigurations (OCR)**			**Industry environment (IE)**		
Variable	Initial	Extraction	Variable	Initial	Extraction	Variable	Initial	Extraction
TD1	1.000	0.747	OCR1	1.000	0.869	IE1	1.000	0.715
TD2	1.000	0.828	OCR2	1.000	0.879	IE2	1.000	0.826
TD3	1.000	0.265	OCR3	1.000	0.891	IE3	1.000	0.861
TD4	1.000	0.254	OCR4	1.000	0.875	IE4	1.000	0.215
TD5	1.000	0.365	OCR5	1.000	0.326	IE5	1.000	0.326
TD6	1.000	0.342	OCR6	1.000	0.432	IE6	1.000	0.301
Perceived Strategic Value (PSV)			**BDA adoption (BDA)**					
Variable	Initial	Extraction	Variable	Initial	Extraction			
PSV1	1.000	0.845	BDA1	1.000	0.848			
PSV2	1.000	0.901	BDA2	1.000	0.743			
PSV3	1.000	0.878	BDA3	1.000	0.521			
PSV4	1.000	0.252	BDA4	1.000	0.432			
PSV5	1.000	0.282						

Source: Author's compilation (2023).

All values below 0.5 in Table 6 are not considered. Hence, these values TD3 (0.265), TD4 (0.254), TD5 (0.365), TD6 (0.342), OCR5 (0.326), OCR6 (0.432), IE4 (0.215), IE5 (0.326), IE6 (0.301), PSV4 (0.252), PSV5 (0.282), BDA3 (0.521) and BDA4 (0.432) are not retained for further analysis. As Eaton et al. (2019) suggested, using stricter cut-off values, balanced with sufficient factors, results in a better model fit and will have varying degrees of goodness of fit. Hence, all the variables with values above 0.7 are deemed a better fit for the model. Thus, the returned values for further analysis are TD1 (0.747), TD2 (0.828), OCR1 (0.869), OCR2 (0.879), OCR3 (0.891), OCR4 (0.875), IE1 (0.715), IE2 (0.826), IE3 (0.861), PSV1 (0.845), PSV2 (0.901), PSV3 (0.878), BDA1 (0.848) and BDA2 (0.743).

4.7. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a multivariate statistical hypothesis-driven structural equation modelling (SEM) technique that investigates the relationship between observed measures or indicators and explanatory variables or factors (Brown, 2015). The study hypothesises the production of a structural equation model (SEM) to measure the correlation between the study variables and the study constructs: Big Data Analytics and sustainable public procurement practices. Unlike the EFA, the CFA can specify the nature of the relationship among the measurement errors of the indicators. CFA uses a rule of thumb that a factor loading of 0.7 or higher represents a sufficient factor for extracting variance from that variable (Eaton et al., 2019). Hair et al. (2014), Chen & Tsai (2007), and Ertz et al. (2016) prescribe a cut-off threshold of 0.6 and above. The CFA was performed to measure the study's assumptions by establishing if there is any correlation between the study constructs and their underlying latent variables. Furthermore, the CFA was used to measure the goodness of fit of the study model. Table 7 shows the confirmatory factor loadings for the study variables.

Table 7: Confirmatory factor loadings.

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			
Perceived Strategic value (PSV)	PSV1	0.88	0.86	0.94	0.874
	PSV2	0.97			
	PSV3	0.93			
	BDA2	0.50			

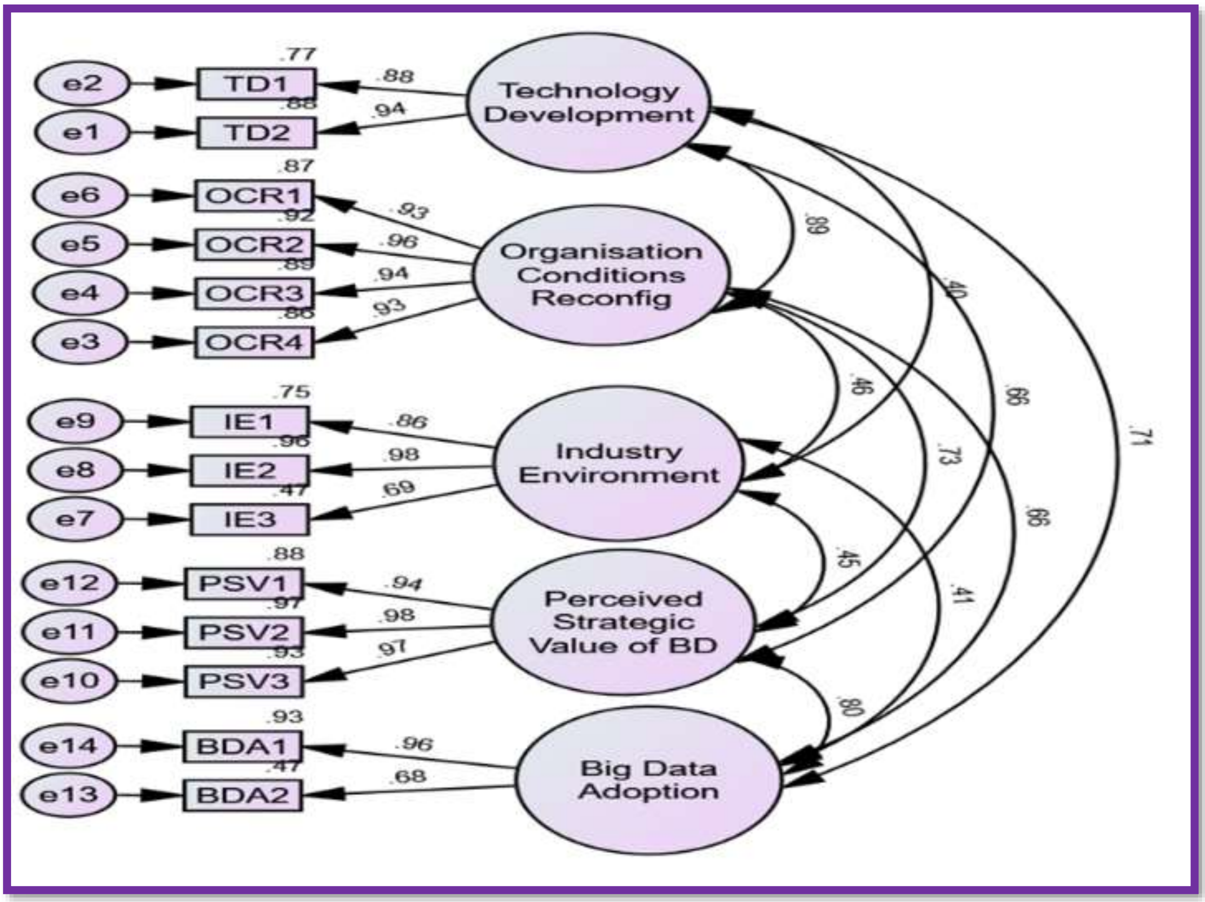
Source: Designed by Researchers.

Table 7 shows that two sub-constructs were measured under the technological development construct. TD1 and TD2 had factor loadings of 0.77 and 0.88, respectively. Under the Organisational conditions and reconfigurations, the study measured four sub-constructs, coded OCR1, OCR2, OCR3, and OCR4, which estimated factor loadings of 0.87, 0.92, 0.89, and 0.86, respectively. The industry environment construct was measured using three sub-constructs. The results show IE1 (0.75), IE2 (0.96) and IE3 (0.47) factor loadings. The study further measured the Perceived Strategic Value construct using three sub-constructs, coded as PSV1, PSV2, and PSV3, which had factor loadings of 0.88, 0.97, and 0.93, respectively. The BDA adoption construct was measured using two sub-constructs. The results are BDA1 (0.49) and BDA2 (0.88). All factors above 0.7 are a good fit. Hence, TD1(0.76), TD2 (0.89), OCR1 (0.87), OCR2 (0.92), OCR3 (0.89), OCR4 (0.86), IE1 (0.75), IE2 (0.96), PSV1 (0.93), PSV2 (0.97), PSV3 (0.88) and BDA2 (0.88) are all fit. However, the factor loadings of IE3 (0.47) and BDA1 (0.49) are below the prescribed threshold.

4.8. Study The Correlation Matrix

The study aimed to understand the relationships between multiple variables. Thus, a correlation coefficient was produced to measure the strength and direction of the relationship between the study variables. The correlation coefficients ranged from -1 to 1, with -1 indicating a perfect negative correlation, 0 meaning no correlation, and 1 indicating a perfect positive correlation. The relationship between the multiple study variables is shown in Figure 3.

Figure 2: Correlation Matrix for the Structural Equation Model:



Source: Designed by Researchers.

The technology development constructs were measured using two variables. TD relation to TD1(0.88) and TD2 (0.94) is above the prescribed value of 0.6. TD relates to OCR (0.89), IE (0.40), PSV (0.66) and BDA (0.71). While OCR was measured using OCR1 (0.93), OCR2 (0.96), OCR3 (0.94), and OCR4 (0.93), the correlations of OCR with the other constructs are IE (0.46), PSV (0.73), and BDA (0.66). IE was measured using three variables, and its relations to the variables are: IE1 (0.86), IE2 (0.98) and IE3 (0.69). IE relates to PSV (0.45) and BDA (0.41). PSV was also measured using three variables, PSV1 (0.94), PSV2 (0.98) and PSV3 (0.97). PSV 805 correlates to BDA. BDA was measured using two variables. The strength of this correlation resulted in BDA1 (0.96) and BDA2 (0.68).

4.9. Study Model fit indices summary

The measurement model fit validates the feasibility of the model statistically, whether it is not fit, acceptable or satisfactory. The study employed a combination of minimum discrepancy per degree of freedom chi-squared, the square error of approximation, goodness-of-fit index, adjusted goodness-of-fit index, normed fit index, comparative fit index, and the Tucker–Lewis index to measure model fit. Table 7 presents the model fit indices, statistical measurements used in this study, to provide information about how well the model fits the data.

Table 8: Measurement model fit indices.

Fit indices	Name	Outcomes	Decision rule	Sources	Decision
CMIN/DF	minimum discrepancy per degree of freedom Chi-squared	DF=3.347 P= 0.000	CMIN/DF<3 indicates an acceptable fit CMIN/DF <5, indicating a reasonable fit	Moss, Lawson and White (2015); Kline (1998) Marsh and Hocevar (1985). Paswan (2009)	Satisfactory
RMSEA	The Square Error of Approximation	0.0720	< .05 indicates a close fit,^ < .08 suggests a good model-data fit.	Moss et al. (2015); Hu and Bentler (1999); MacCallum, Browne and Sugawara (1996) Steiger and Lind (1980)	Satisfactory
Gfi	Goodness-of-Fit Index	0.865	> 0.9 indicates good levels of fit	Xia and Yang (2018) Hayashi, Bentler, and Yuan (2011). Hu and Bentler (1999) Bentler and Bonett (1980)	Acceptable
AGFI	Adjusted Goodness-of-Fit Index	0.797			
NFI	Normed Fit Index	0.930			
CFI	Comparative Fit Index	0.950			
TLI	Tucker–Lewis Index	0.935			

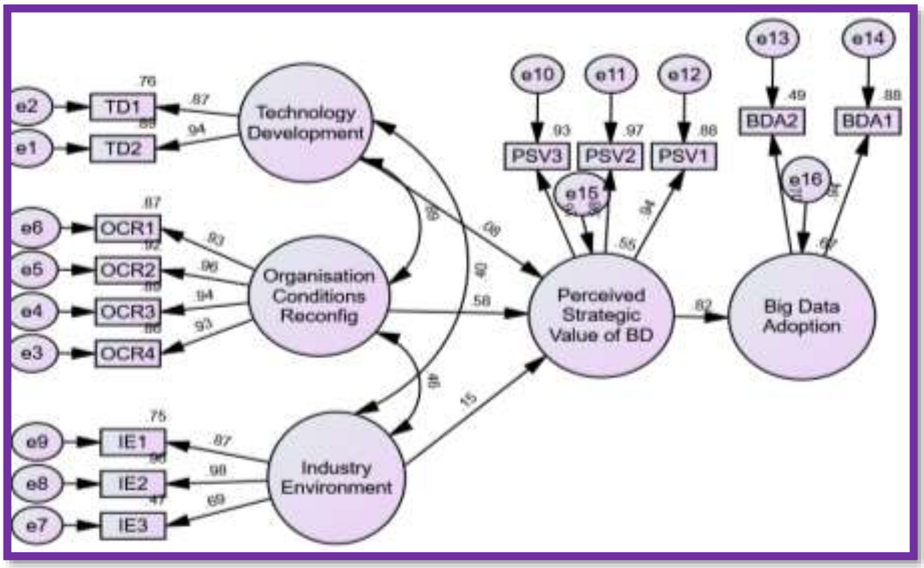
Source: Designed by the Researchers.

A good model fit is crucial because it indicates that the model accurately represents the relationships between variables in the data being analysed. The study CMIN/DF shows the minimum discrepancy per degree of freedom in the chi-squared distribution. According to Kline (1998) <3 Validates an acceptable fit between the conceptual framework and data, while CMIN/DF <5 indicates a good fit (Marsh & Hocevar, 1985). Furthermore, Paswan (2009) suggests that a value 2< CMIN/DF<5 is acceptable for the study model. The study CMNI/DF yielded a satisfactory outcome of 3.347. Before deciding that the hypothesised model fits the observed data reasonably well, the Root Mean Square Error of Approximation (RMSEA) must be measured (Steiger & Lind, 1980). RMSEA calculates the square root of the population misfit per degree of freedom (Hayashi et al., 2011). When the RMSEA value is low, the fit is good, and when it is high, the fit is poor (Hu & Bentler, 1999). The observed RMSEA index is 0.0720, which indicates a close fit. The GFI, AGFI, NFI, CFI, and TLI cut-off values are all set at 0.9 and range from 0 to 1, as recommended by Hayashi et al. (2011), Xia and Yang (2018), Hu & Bentler (1999), and Bentler & Bonett (1980). Xia & Yang (2018) suggest that the higher the result, the better the model. The Goodness-of-Fit Index (GFI) was used to compare alternative CMNI/DF outcomes. GFI computes the percentage of variance explained by the approximated explanatory variables. The GFI indices resulted in a value of 0.865, indicating a good fit and an acceptable level (Hu & Bentler, 1999). This means that 86.5% of the study variables are explained. To adjust the GFI index, the researchers examined the Adjusted Goodness of Fit Index (AGFI), which corresponds to the squared multiple co-variances adjusted for altered degrees of freedom (Hayashi et al., 2011). The fit is good when the value of AGFI is close to 1. However, AGFI is never greater than or equal to GFI. The AGFI result of 0.797 is acceptable and reasonably fits the model (Hayashi et al., 2011). The Normed Fit Index (NFI) reflects the proportion by which the study model improves the fit between the saturated model (TS = 0) and the independence model (TI), as noted by Hayashi et al. (2011). NFI can still be defined even when T is a descriptive statistic with unknown dispersion. The NFI index results are 0.93, indicating an acceptable model fit. Tucker–Lewis index (TLI), also known as the Non-Normed Fit Index (NNFI), is comparable to the NFI, except that the TLI compensates for the influence of model complexity (Hu & Bentler, 1999) and is relatively independent of sample size. The result is 0.935, which is an acceptable model fit, as suggested by Hu & Bentler (1999) and Hayashi et al. (2011). Lastly, the study examined the Comparative Fit Index (CFI), defined by population non-centrality parameters (Hayashi et al., 2011). CFI avoids NFI underestimation and TLI overestimation, making it the most commonly observed index. The CFI was observed to be 0.950, making it acceptable. The model fit indices result indicates that the data fit the model well.

4.10. Structural Equation Modelling

Structural equation modelling (SEM) is a multivariate statistical technique for testing and estimating relationships among variables (Lowry & Gaskin, 2014). The study examined the relationships between latent (unobservable) constructs and observed variables to test hypotheses and evaluate the overall fit of a model to the data. SEM employs a set of calculations to assess the relationships between variables and the model's accuracy. These calculations include path coefficients, which measure the strength and direction of the relationships between variables; collinearity, which indicates the degree to which variables are correlated with each other; Coefficient of Determination (R2), which refers to the percentage of the variability in the dependent variable that is accounted for by the independent variables; total effect, which combines direct and indirect effects of the independent variables on the dependent variable; and effect size, which measures the magnitude of the relationship between variables. These calculations evaluate the model's fit to the data (Hair et al., 2014). Figure 4-4 shows the study's SEM output. The model suggests that technological development, organisational conditions, reconfiguration, and industry environment influence BDA's perceived strategic value. If BDA is perceived as strategic and valuable, it facilitates the adoption of BDA, which in turn promotes sustainable public procurement practices.

Figure 2: The structural model.



Source: Designed by Researchers.

In the structural model used in this study, loading factors were employed to illustrate the significance of the relationships between the constructs and variables under examination. Some of the variables had low factor loadings. However, these were not ignored because the fact that all values were above 0 indicated that there was evidence of a relationship between the variables. Additionally, various statistical tests, including reliability statistics, discriminant validity, confirmatory factor analysis, exploratory factor analysis, p-values, and study model fit indices, were used to evaluate the adequacy of the model. These tests provided further support for the validity of the model.

Technological development (TD) was measured using two variables, namely ICT infrastructure (TD1) and Scalability (TD2). The factor loadings for TD-measured variables were all positive, indicating a significant relationship. TD1 (0.87) and TD2 (0.94) are all above the acceptable threshold of 0.6, as prescribed by Hair et al. (2014). TD1 and TD2 are, therefore, suitable for measuring technological development. Furthermore, it is inferred that technological development has a positive influence on the perceived strategic value of BDA (PSV), as measured by a factor loading of 0.08. Although this loading is not strong, the fact that it is above 0 suggests it has an effect. The model also indicates that TD affects OCR (0.89) and IE (0.40). Thus, the interrelationship between the constructs suggests a well-connected model. From these findings, TD influences BDA's perceived strategic value, which in turn impacts BDA adoption, ultimately transforming SPPP.

Organisation conditions and reconfigurations: Management commitment (OCR1), staff capabilities (OCR2), procurement structures (OCR3), and change management (OCR4) are the variables used to measure the organisation's conditions and reconfigurations (OCR). The factor loadings on these variables and their influence on OCR are all above the cut-off value, as shown on OCR1 (0.93), OCR2 (0.96), OCR3 (0.94) and OCR4 (0.93). The researcher further examined whether OCR impacts PSV, which measured 0.58, indicating that OCR influences the perceived strategic value of BDA by 58%. The study measured the interdependence between constructs, and OCR influences TD (r = 0.89) and IE (r = 0.46).

The industry environment was measured using the legal framework (IE1), risk management (IE3) and business partners' readiness to support (IE2). IE1, IE2 and IE3 influence the industry environment by 87%, 98% and 69%, respectively. The study also examined the relationship between the industry environment and its impact on the perceived strategic value of BDA. The results indicated that IE influences the perceived strategic value of BD by 15%

The perceived strategic value (PSV) of BD was measured using three variables: Procurement analytics (PSV1), transformed into a strategic function (PSV2), and Integrations (PSV3). The correlations between PSV and PSV1 (0.9), PSV2 (0.55), and PSV3 (0.97) exceed the cut-off values. Furthermore, it was established that PSV influenced BDA adoption by 82%

4.11. Hypothesis Testing

Low & Meghir (2017) and Bagozzi & Yi (2012) discuss the usefulness of structural modelling in research. Low & Meghir note that the structural model shows the proposed research model and the connections between the main variables. Bagozzi & Yi (2012) add that the structural model can be used to test hypotheses and evaluate the model's fit to the data. These sources suggest that structural modelling is essential for understanding variable relationships and trying to accept or reject the predicted associations between variables. Below are the research hypotheses tested. Weiss (2010) suggests that a p-value less than 0.05 is commonly considered statistically significant, indicating strong evidence against the null hypothesis. Table 4-15 summarises the results of the study hypotheses testing, highlighting the essential findings and any substantial relationships or patterns that were discovered.

Table 9: Hypothesis testing.

Hypothesis	Path	Path coefficient	*P* value	Decision
H1	TD-PSV	0.80	0.0537	Supported
H2	OCR-PSV	0.58	0.00	Supported
H3	IE-PSV	0.15	0.04	Supported
H4	PSV-BDA	0.82	0.00	Supported

Source: Designed by Researchers.

The results indicate that technological development (TD) does positively influence the BDA perceived strategic value (PSV) (β = 0.80, p = 0.0537). In contrast, Organisation Conditions and Reconfigurations (OCR) (β = 0.58, p = 0.00) and Industry Environment (IE) (β = 0.15, p = 0.09) positively influence the BDA perceived strategic value (PSV). Moreover, BDA perceived strategic value (PSV) positively impacts the Big Data Adoption (BDA) (β = 0.82, p = 0.00). The structural model results supported H2, H3 and H4 and did not support H1, as shown in Table 9.

4.12. Discussion of Findings

The study postulated four hypotheses using the TOE factors to unearth the Namibian government's readiness to adopt BDA in public procurement. The study hypothesises the TOE factors to establish readiness. The findings are discussed below. The technological development has a positive influence on the BDA's perceived strategic value (H1). The study results support H1, indicating a positive relationship between technology development and the perceived strategic importance of BDA. The findings reveal that Namibia has an adequately developed ICT infrastructure and has invested heavily in expanding its broadband network. The government has also implemented various initiatives to promote the use of technology in public procurement, such as the Namibian E-GP system. Therefore, from a technological readiness perspective, Namibia appears well-prepared to adopt BDA in public procurement.

The study demonstrates that technological development has a positive influence on the BDA's perceived strategic value. Thus, H1 was supported. Cronbach's Alpha reliability test was used to evaluate the construct validity, and factor loadings were used to assess the convergent validity. Cronbach's Alpha values range from 0.890 to 0.842, which implies reasonable reliability of the scales. The explanatory factor was used, and only study variables with loading elements above the prescribed level were considered for further analysis. Technological development is considered to have two variables with factor loadings of ICT infrastructure (0.747) and scalability (0.828). Both factors passed the confirmatory factor loadings and were fit for structural modelling. The technology's development has a beneficial impact on BDA's perceived strategic value. A factor loading of 0.08 is used to calculate this value. While this loading is not significant, the fact that it is greater than 0 indicates that there is an influence. The model also suggests that TD has an impact on OCR (0.89) and IE (0.40). Thus, the interdependence of the constructs means a well-connected model. The findings supported the view that TD influences BDA's perceived strategic value, which affects BDA adoption, thereby transforming SPPP.

The organisation conditions and reconfigurations positively influence the BDA’s perceived strategic value (H2). The study results support H2, indicating a positive relationship between organisational readiness and BDA’s perceived strategic importance. Management commitment (OCR1), staff capabilities (OCR2), procurement structures (OCR3), and change management (OCR4) are the variables used to measure the organisation's conditions and reconfigurations (OCR). The factor loadings on these variables and their influence on OCR are all above the cut-off value, as shown on OCR1 (0.93), OCR2 (0.96), OCR3 (0.94) and OCR4 (0.93). The researcher further looked at whether OCR impacts PSV, which measured 0.58. Thus, OCR influences the perceived strategic value of BDA by 58%. The study measured the interdependence between constructs, and OCR influences TD ($r = 0.89$) and IE ($r = 0.46$). This means that the readiness of the Namibian public procurement organisations to adopt BDA is mixed.

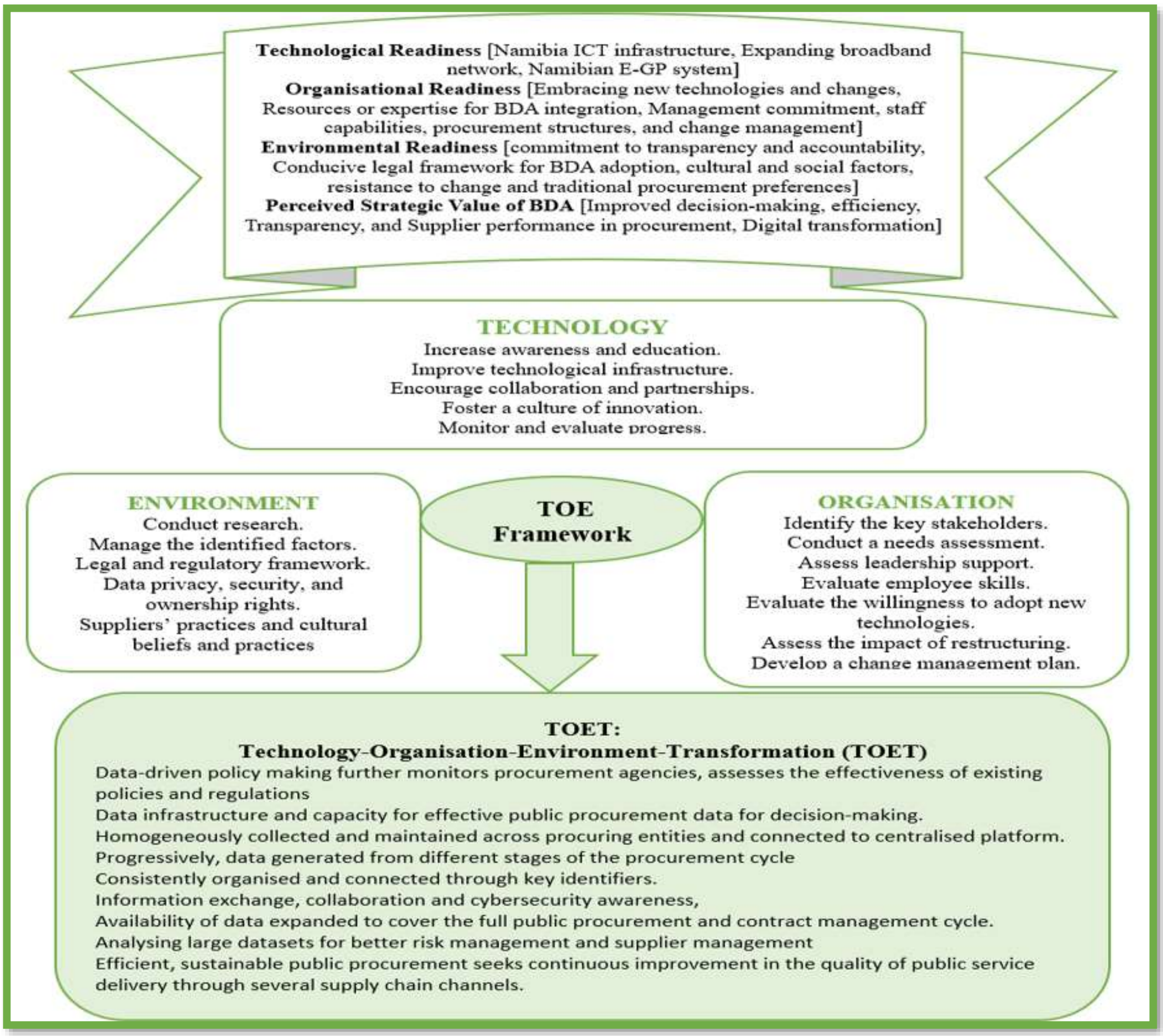
Although some organisations are willing to adopt new technologies and change workplace cultures and practices, others may need more resources or expertise to integrate BDA effectively into their procurement processes. The study also reveals the existence of resistance to change within some organisations, which could slow the adoption of BDA. Additionally, the research underscores the need for increased practice, capacity, and expertise from a human resource perspective. Therefore, organisational readiness in Namibia may be a limiting factor in adopting BDA in public procurement.

The industry environment has a positive influence on the BDA's perceived strategic values (H3). The results of the study support H3. The environmental factors affecting the adoption of BDA in public procurement in Namibia are generally favourable. The government has committed to promoting transparency and accountability in public procurement through various initiatives, including the introduction of a new Procurement Act in 2015. This suggests that the legal framework environment is conducive to the adoption of BDA in public procurement. The study also examined the relationship between the industry environment and its impact on the perceived strategic value of BDA. The results indicated that IE influences the perceived strategic value of BD by 15%. However, cultural and social factors could affect the adoption of BDA, such as resistance to change or a preference for traditional procurement methods from the supply market.

The BDA's perceived strategic value has a positive influence on SPPP adoption (H4). Study results support this hypothesis. Study findings reveal that the adoption of BDA could provide significant strategic value. Improved decision-making could be particularly valuable in a country where procurement decisions have been criticised for being inefficient and opaque. By offering insights into historical procurement data, BDA can help public entities identify patterns and trends that inform future procurement strategies. This could lead to improved decision-making and more excellent strategic value. The study affirms that manual and time-consuming processes characterise the Namibian procurement processes, consequently slowing the procurement process and reducing efficiency. The study suggests that using BDA will enable the automation of the procurement process, saving time and freeing up resources for more strategic functions, ultimately increasing efficiency and delivering excellent strategic value in public procurement. Thus, recognising this value, the study found that PSV influences BDA adoption by 82%, thereby transforming SPPP.

The technology readiness in Namibia is a vital factor supporting the adoption of BDA in public procurement. However, organisational readiness may be a limiting factor, as some public procurement organisations may need more resources or expertise to integrate BDA effectively. The environmental factors are generally favourable, although cultural and social factors could slow the adoption of BDA. Adopting BDA in Namibian public procurement could provide significant strategic value, particularly in improved decision-making, increased efficiency, enhanced transparency, and supplier performance. By adopting BDA, Namibian public procurement organisations could gain a competitive advantage and increase public trust in the procurement process.

***Figure 5: Extension of the TOE Framework to the TOET Framework*.**



Source: Designed by Researchers.

4.13. Theoretical And Managerial Implications

The study utilised the Technology-Organisation-Environment (TOE) framework and Information Processing theory to evaluate the influence of Namibian T-O-E Factors on the perceived strategic value of big data analytics for Sustainable Public Procurement. The adoption of BDA in public procurement has the potential to improve the efficiency, transparency, and effectiveness of public procurement processes, ultimately leading to more sustainable procurement practices. The study provides a conclusion on the evaluation of the Namibian TOET factors' readiness to adopt BDA in public procurement. Big Data analytics enhances public procurement transparency, accountability, and citizen engagement by enabling government departments, service providers, and institutional structures to communicate effectively with citizens, solicit feedback and feedforward, and monitor and deliver public service practices in real-time. Big Data analytics holds immense potential for driving innovation, improving decision-making, and enhancing societal well-being across various sectors (Huber et al., 2019). By leveraging the power of data and analytics, organisations and policymakers can address complex challenges, unlock new opportunities, and create positive societal impact for sustainable public procurement practices.

The transformative Big Data analytics holds immense promise for driving innovation, enhancing decision-making, and fostering societal progress across various domains (Bergman, 2023). By harnessing the power of data and analytics, organisations and policymakers can unlock new insights, optimise processes, and create value for individuals and communities (Titl et al., 2019). From personalised medicine to smart cities, Big Data analytics has the potential to revolutionise public procurement practices, advance developmental technology, improve industry efficiency, and address complex public procurement challenges facing society, such as data quality, skill gap, collaboration and TOE factors.

Data analytics enables agencies to assess existing efficiency gaps and understand the drivers of performance; these empirical insights are useful for identifying and prioritising potential areas for intervention and reform efforts (World Bank, 2020; Bergman, 2023). An appropriate data infrastructure and capacity are necessary for effectively utilising public procurement data for informed decision-making. This means that procurement data should be collected and maintained uniformly across procuring entities and connected to a centralised platform (Bosio et al., 2022). Progressively, data generated from different stages of the procurement cycle (for example, tendering process, bidding process, bid evaluation, contract award, and contract signing) should be consistently organised and connected through key identifiers. Despite the magnitude of information exchange, collaboration, and cybersecurity awareness, the availability of data should be expanded to encompass the entire public procurement and contract management cycle (OECD, 2021).

Ultimately, efficient, sustainable public procurement seeks continuous improvement in the quality of public service delivery through several supply chain channels, such as the selection of higher-quality goods, more flexible, timely delivery of goods and completion of inclusive socio-economic public infrastructure, and better predictive demand planning of purchases, data-driven decision making, and agile asset and stock management (Wachs et al., 2021). Public procurement data increases transparency and accountability, making it easier to detect and prevent irregular spending, corruption, and other unethical practices. This, in turn, enhances accountability and ensures that public funds deliver maximum value (Decarolis et al., 2022). Data-driven policy making further monitors procurement agencies, assesses the effectiveness of existing policies and regulations, and then informs the development of new policies or refinements to existing ones to better meet objectives such as cost savings, integrity, responsiveness, resilience, and sustainability (Fazekas et al., 2020). Given these strategic functions, efficient and effective public procurement can contribute to the achievement of the development goals of ending poverty and promoting shared prosperity to meet some UN SDGs.

4.14. 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 impact on Namibia's public procurement entities, including the Central Procurement Board, the government, and the PPU. By leveraging data analytics, they can shape sustainable policies, monitor compliance, enhance stakeholder engagement, allocate resources more efficiently, and foster global collaboration in sustainable procurement practices.

4.15. 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.

4.16. Limitations

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

5. 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. This journey involves fostering a data-driven decision-making and innovation culture, shaping a resilient, efficient, and responsible future for the country's procurement sector. The study concludes that BDA has a significant potential to enhance SPPP when implemented effectively and efficiently.

5.1. 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 sustainable procurement effectiveness. This research lays the groundwork for future exploration and identifies opportunities for further investigation.

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