The Significance of Big Data Analytics in the Procurement Process and Supply Chain Management in the Nigerian Manufacturing Industry

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ABSTRACT

The adoption of BDA in Nigeria faces challenges due to the absence of affordable computing, mining, reliable data, and weak institutional frameworks in many organisations. It is important to examine the significance of BDA in the procurement process and SCM in the Nigerian manufacturing industry (NMI). The study employed multiple case study sampling method, linear curve estimation (LCE), Cronbach's alpha, and exploratory factor analysis (EFA) for the analysis of the data. The results showed that BDA contributed significantly to the increase in the procurement process by 65.3% and the increase in SCM by 48.4% in NMI. Further estimations to examine interconnectivity among the complex structures in SCM revealed that efficient procurement processes, SC visibility, and SC flexibility of NMI had positive and significant influence on SC resilience. Strong reliability was shown by the majority of scale items, which had Cronbach's alpha coefficient values greater than 0.7 but less than 0.90. The outcomes of factor analysis indicated that the pattern matrix displayed significant factor loading and a high connection between factors. The study concluded that BDA is significant in the procurement process and SCM in the Nigerian manufacturing industry. Therefore, agreeing with knowledge management and competitive advantage theories that companies process diverse data to ensure efficient operations and market differentiation to improve competitive edge, customer satisfaction, and brand loyalty in the industry. The study provides valuable insights for practical policy implications.

Keywords: Supply chain management, procurement process, big data analytics, knowledge management, competitive advantage.

INTRODUCTION

The manufacturing sector in Nigeria (NIM) contributed ₦25,725.87 billion to the country's GDP in 2021 (Central Bank of Nigeria [CBN], 2022). The Nigerian economy is considerably dependent on this industry. It significantly contributes to creating jobs, raising productivity, and promoting economic progress. The industry is significant since it creates jobs and increases tax income for the government, all of which significantly boost GDP. It has been acknowledged that the industry is significant to the nation's attempts to diversify and wean itself off of its oil dependency. The industry will assist the country in improving its trade balance, lowering its reliance on imports, and increasing its level of overall competitiveness. As a consequence of Industry 4.0, the manufacturing industry is anticipated to experience significant transformations, one of them being the integration of supply chains (SCs) through real-time data interchange facilitated by information and communication technology (Aslan, 2020). Big data analytics (BDA) has the potential to contribute significantly to the procurement process and supply chain management (SCM) of NIM. While one of the biggest issues Nigerian manufacturers are currently facing is the lack of stable infrastructure, other issues include power outages, inadequate road networks, and restricted access to ports and airports, which make it difficult for businesses to transport goods and raw materials both domestically and internationally. This results in an increase in lead times and costs and a decrease in competitiveness among firms. Smart factories rely on BDA and sophisticated data gathering techniques to enable a high degree of automation in industrial activities. These factories are fully connected to buildings and information systems (Chumnumporn et al., 2019).

Trade flows have been disrupted, SC risk increased, and restrictions were imposed as a result of the crisis between Russia and Ukraine. These have an impact on the flow of the required raw materials, which calls for an innovative procurement process. Big data (BD) is necessary to improve SC efficiency, response time, risk assessment, and customer requirement forecasting; BDA assists in coordinating sourcing strategies to meet long-term objectives (Awwad et al., 2018; Bienhaus & Haddud, 2018). BD plays a significant role in procurement, assisting companies in improving performance and decision-making. It assists companies in reducing supplier disruptions, increasing SC visibility, optimising inventory levels, and locating new suppliers. BDA capability reduces the bullwhip effect in SCM by favourably influencing SC flexibility (Srimarut & Mekhum, 2020; Hsu et al., 2021). This helps companies take quick decisions that will make them more resilient to setbacks (Liu et al., 2023). BDA enhances the SC visibility, flexibility, and resilience, which are essential elements of SCM. There is a research gap in this area since most of the existing studies were carried out in the developed countries.

There is emphasis on the motivation for more affordable computing, mining, reliable data, etc. as the advantages that drove the adoption of BDA in procurement and SCM (Rejeb et al., 2018). The absence of these elements is one of the potential obstacles that the majority of Nigerian organisations are facing when implementing BDA in SCM. Additionally, it is critical to understand the problem from a Nigerian perspective because of institutional structures and norms that are different from those of other industrialised nations. According to Abor and Fiador (2013), institutional blockholders govern businesses in sub-Saharan African countries like Nigeria, and the corporate environment is characterised by shaky and occasionally fragmented regulatory frameworks. The institutional differences hypothesis states that developed and developing countries have different institutional frameworks that create differences in risk management costs (Julian & Ofori-Dankwa, 2013). On that note, it is necessary to investigate the significance of BDA in the procurement process and SCM in the NMI. To the best of study knowledge, no research has been carried out in this area in Nigeria, and ascertaining this impact in NMI is noteworthy given the role of the industry in the growth of the national economy. The average capacity utilisation in the industry continued to decline, despite being the second-highest contributor to GDP behind the agriculture sector (CBN, 2022). Furthermore, Nigerian manufacturing value added as a proportion of GDP was 15% as of 2021 (World Bank, 2023). This disclosure highlights the necessity to investigate the significance of BDA in the procurement process and SCM in the NMI.

LITERATURE REVIEW

Supply Chain Management

The production and delivery of goods and services are organised and controlled through SCM, which encompasses a variety of roles played by the stakeholders in order to accomplish shared objectives (Stock & Boyer, 2009). Fan and Stevenson (2018) contend that SCM works to maximise the SC in order to lower expenses, increase output, and boost customer satisfaction. To ensure a consistent flow of goods and services, SCM combines purchasing, inventory management, delivery, logistics, production, and transportation (Mentzer et al., 2001; Sweeney, 2011). SCM consists of inbound and outbound SCs, with outbound concentrating on creating, transferring, and delivering commodities. While inbound SC is designing products, locating parts, and controlling workspace, apparatus, and supplies for operations (Lejeune & Yakova, 2005). Material flows from pre-manufacturing to customers are included in standard SCM models. SCs are complex networks with inherent risks. Reducing, controlling, and forecasting risks effectively can give businesses a competitive edge (Siong Kuik et al., 2011; van Bommel, 2010; Konecka, 2010). Efficient SCM can provide an advantage over competitors by reducing expenses, boosting output, and enhancing customer contentment (Lejeune & Yakova, 2005). SCM effectively fosters talent development and integrates linkages, with rivalry impacting advancement and pursuing leaner instruments and flexibility for long-term success (Konecka, 2010; Krishnapriya & Rupashree, 2014). For lean or agile frameworks to be effective, high product quality and short lead times are necessary (Christopher, 2000). These frameworks rely on variety, variability, and volume (Anatan, 2006).

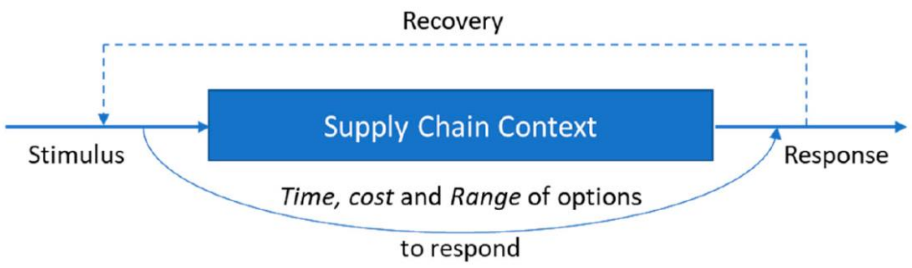
The requirement for SC agility is driven by the rising rate of change and volatility in the corporate environment (Ismail & Sharifi, 2006). Legislation has been enacted in response to environmental concerns, with a focus on improving organisational accountability and sustainable management approaches (Xie et al., 2015). Sustainability is a crucial factor to consider if you want to create a sustainable competitive advantage, regardless of whether your focus is on lean (efficient and waste-free) or agile (rapid and responsive to market demands). Lean SCM is suitable for corporate environments that are stable, predictable, and under control (Ciccullo et al., 2018). In contrast, an organisation needs the agile paradigm to function in a setting where market swings are unpredictable. On that note, BDA can help organisations increase the visibility, flexibility, and resilience of their SC to better adapt to changes and uncertainties in the SC. BDA capabilities have a positive and significant impact on SC performance (Mandal, 2019; Dubey et al., 2019; Srimarut & Mekhum, 2020). BD enablers can reduce the bullwhip effect, a major issue in SCM, which enhances SC performance and agility (Hsu et al., 2021).

SC visibility enables businesses to create logistical predictive metrics, diagnostics, forecasts, and physical asset descriptions by tracking and observing the movement of raw materials to finished products. As a result, productivity rises, shortages are avoided, and client demand is precisely estimated (Hunaid et al., 2022; Singagerda et al., 2022; Kalaiarasan et al., 2022). Performance of a company is greatly impacted by SC visibility since it makes it possible to regulate deviations and have a better understanding of inbound logistics. Implementing SC visibility enhances real-time information access, collaboration, decision-making, risk monitoring, and predictive capacities (Singherda et al., 2022; Goswami et al., 2013). Boile and Sdoukopoulos (2014) contend that whereas SC visibility helps businesses, sharing private information with various parties increases the danger of data breaches. Freichel et al. (2022) affirm that mutual trust is necessary for establishing SC visibility to reduce impediment to communication, resulting in subpar distribution and logistics performance.

Flexibility in the SC encompasses quick market, supply, and demand changes, enabling flexible supply networks to continue operating. A flexible SC prioritises agility and speed to facilitate prompt and sensitive decision-making (Tukamuhabwa et al., 2015). Wang et al. (2016) emphasise that by evaluating SC performance in demand planning, purchasing, production, inventory, and logistics, SC flexibility increases operational efficiency. The flexibility of a business is contingent upon its capacity to promptly address changes in demand, encompassing both volume and diversity. SC flexibility depends on market conditions (Tukamuhabwa et al., 2015; Christopher, 2000; Anatan, 2006). SC flexibility looks at future demand, procurement procedures, and expenditure patterns to match sourcing strategies with strategic objectives. It assesses supplier inputs, supply market trends, and economics to facilitate efficient sourcing tactics (Wang et al., 2016). The structural flexibility method provides flexible options for SC design in a corporate environment that is evolving quickly (Christopher & Holweg, 2011; Ismail and Sharifi, 2006).

SC resilience is the capacity of a business to promptly resume normal operations following an interruption. The necessity for SC resilience stems from the severity and frequency of SC disruptions, which have been exacerbated by the elevated level of uncertainties and contextual factors (Bahrami et al., 2022). Kopanaki (2022) claims that robust SCs are equipped to act fast in dealing with unanticipated circumstances and carry on with business as usual following a disruption. Bayramova et al. (2021) posit that SC resilience is the ability of SC to increase readiness against unanticipated disruptions, adapt quickly, and recover to their prior condition, or preferably to a better one. Kopanaki (2022) affirms that controlling supply fluctuations, adjusting production volume and capacity, making swift modifications to product designs, and launching a variety of marketing initiatives are all parts of managing resilience in the SC. The basic phases of SC resilience include anticipation (proactive planning and thinking), response (rapid and effective reactions), resistance (preserving structure and function), and recovery (Bahrami et al., 2022).

Figure 1: Supply Chain Resilience Framework



Source: Adopted from Kopanaki (2022)

Long-term strategic investment is necessary to build resilience, which is essential for strategic enterprises to prosper in competitive situations (Ozdemir et al., 2022; Bahrami et al., 2022). Kopanaki (2022) asserts that a conceptual framework for the stimulus-response model was developed as the primary example of SC resilience, as seen in figure 1. Three steps can be conceptualised as constituting SC resilience: the initial disruption (stimulus), the response (reaction), and the recovery (to the initial or new stable state).

Procurement

Procurement is the act of purchasing products, services, or works from an outside source. It can provide you with a competitive advantage and is a crucial part of SCM (Tripathi & Gupta, 2021; Heckman, 2003). Procurement entails identifying needs, selecting suppliers, negotiating terms, and buying products or services from vendors while weighing sustainability, quality, cost, and dependability (Ameh & Ogunyemi, 2015; Furneaux & Barraket, 2014). Procurement specialists help in cost control, negotiate fair terms, and lower SC risks through assessing risks, verifying supplier adherence, and developing backup plans (Hasan & Habib, 2022). Procurement plays a crucial role in SCM by assisting organisations in choosing the right goods and services using ideas such as organisational strategy, competitive advantage, marketing, anti-corruption, sustainability, and social equity theory (Gunasekara et al., 2022; Strang, 2014).

Organisational strategy theory enhances project efficacy and performance by coordinating principles with preferred procurement processes (Chong & Preece, 2014). The theory of competitive advantage highlights the significance of procurement in enhancing the competitive edge of an organisation. It underlines the need to integrate procurement into corporate strategy and focus on cost leadership and differentiation (Bulbeck, 2010). Anti-corruption capabilities theory looks at how well e-procurement technologies work to reduce corruption, while marketing theories mimic business demand in procurement decision-making (Strang, 2014; Neupane et al., 2015). Social equality and justice theories, on the other hand, support social justice and equity through tactical measures such as socially responsible public procurement (Gyori, 2022). Sustainability theories support green procurement and environmental impacts (Khahro et al., 2021).

The use of unique resources and talents can help a business stand out from competitors and create a long-lasting competitive advantage (Grant, 1991). It is critical to keep in mind that a competitive edge could evolve over time. Because of this, companies need to develop and adapt all the time to stay ahead of the competition (Peranginangin, 2015). Engelbrecht-Wiggans and Katok (2006) assert that procurement enhances competitive advantage through non-competitive purchasing, auctions, value chain optimisation, supplier relationships, and customer loyalty. Costs can be optimised, customer satisfaction can be raised, and a competitive advantage can be gained by analysing upstream and downstream value chains (Mwashegwa & Nondi, 2019; Loice, 2015; Wang & Peng, 2010). Tai (2018) affirms that well-established manufacturing organisations can gain a competitive edge in direct procurement by improving interorganisational management capabilities. This includes improving supplier alignment, information interchange, and monitoring through web-enabled direct buy.

Big Data Analytics

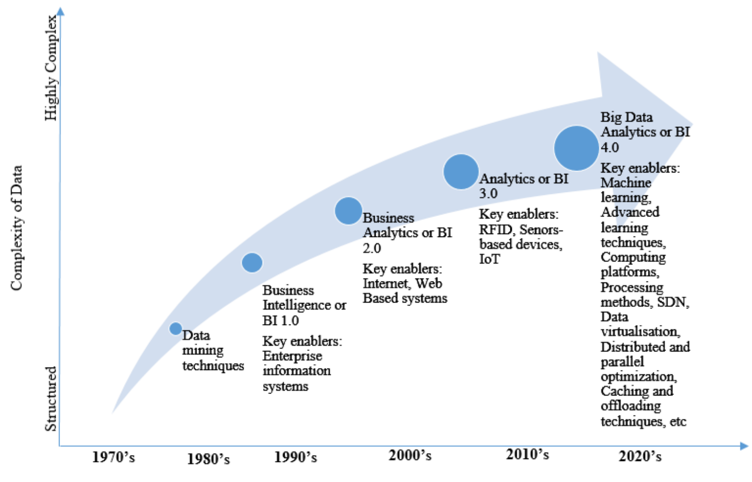
BDA involves analysing large, complex data sets utilising state-of-the-art analytical techniques in order to obtain insightful knowledge. BD is a constantly expanding body of information that presents usage, storage, and analytical issues for industrial organisations (Addo-Tenkorang & Helo, 2016). Yu et al. (2021) posit that BDA has the potential to enhance decision-making by increasing the processing capacity required for data processing, analysis, and improvement from several sources. BDA examines complex data sets to find hidden patterns, correlations, and insights for improved decision-making by utilising tools like processing, real-time analysis, querying, and sophisticated analytical methodologies (Chen et al., 2012; Kumaraguru & Chakravarthy, 2017; Bansal et al., 2022). Gopal et al. (2022) define BD using five criteria: velocity, volume, value, variety, and veracity for data quality and correctness.

BDA requires drawing conclusions from the data in order to find trends and correlations that can be utilised to inform decisions. The theories of BDA encompass a broad variety of topics, including what drives BDA adoption, why it occurs, and how it affects corporate performance (Zaman et al., 2021; Lutfi et al., 2022; Chatterjee et al., 2022). There are many theoretical frameworks, such as the technological-organisational-environmental (TOE) theory, the technology acceptance model (TAM), institutional theory, complexity leadership theory, organisational climate theory, and knowledge management theory, which have been used to study the adoption of BDA. The TOE paradigm takes into account technological, organisational, and environmental aspects in the adoption of BDA (Mezghani et al., 2022; Ganeshkumar et al., 2023; Al Hadwer et al., 2021).

The TAM looks at the attitudes of people toward adopting technology, with a particular emphasis on perceived utility and simplicity of use (Bryan & Zuva, 2021). Institutional theory asserts that interactions and regulations inside institutions determine behaviour, which in turn influences the adoption of BDA (Korsakienė et al., 2015; Ab Talib et al., 2016; Felin & Foss, 2019; Mezghani et al., 2022). Complexity leadership theory underscores the significant role of leadership in successful technology adoption (Moors & Rogiest, 2019; Danaher, 2021), and organisational climate theory examines employee attitudes and perceptions (Dzansi et al., 2014). Knowledge management theory proposes that BDA enhances knowledge management practices, increasing efficacy and performance (Sekli & Vega, 2021). BDA improves performance and decision-making by converting data into insightful knowledge through knowledge management. This leads to better decision-making, higher productivity, better customer experiences, competitive advantage, and cost savings (Ferraris et al., 2019; Muhammad, 2022).

BDA has evolved dramatically, moving from on-premises to cloud systems and emphasising the value of data analysis (Miladinovi et al., 2022). The evolution of BDA is shown in Figure 2. Arunachalam et al. (2018) claim that BDA has the ability to completely transform knowledge through exploration of industrial big data and lifelong knowledge. BDA revolutionises business decision-making and improves performance across industries through the provision of untapped insights and data (Sazu & Jahan, 2022; Ganeshkumar et al., 2023; Miladinović et al., 2022; Weng, 2020). Arunachalam et al. (2018) affirm that this change has been facilitated by the BD era, which is driven by SC technologies, a wealth of data, and managerial emphasis on making decisions based on data.

Figure 2: Evolution of Big Data Analytics



BDA helps businesses better understand their customers, create customised goods, find ways to cut costs, increase customer loyalty and satisfaction, and spot inefficiencies. In addition, it aids companies in standing out from the competition (Muhammad, 2022; Willetts et al., 2020). BDA is important in manufacturing, supply chain management, and planning for green infrastructure. BDA is an effective method for handling the SC and, in turn, expanding variety and volume of data (Biswas & Sen, 2016).

Big Data Analytics and Procurement Process

BDA enhances procurement processes by offering insights, strengthening decision-making, streamlining supplier management, and boosting competitive edge. Bulgakov and Makarenko (2022) propose an integrated system for monitoring the external environment with an emphasis on internal procurement management and utilising BDA and a risk-orientated methodology for increased effectiveness. The concept of procurement 4.0 has changed to meet new business needs and provide new value propositions. Emerging technologies, like the Internet of Things (IoT), robotic process automation (RPA), big data and cognitive analytics, artificial intelligence (AI), and cloud technologies, among others, can be utilised to integrate Industry 4.0 principles with procurement (Chandrasekara et al., 2020). BDA enhances procurement by enhancing supplier management, decision-making, risk management, and efficiency through data analysis and contract negotiations (Biazzin & Carvalho, 2019). The application of BDA in the procurement process increases efficiency and reduces costs. For instance, Li et al. (2020) used BDA to accurately forecast changes in copper prices by employing the procurement strategy for raw materials based on copper used in plant construction.

Similarly, Queiroz and Telles (2018) highlight that one common BDA application in procurement is predictive analytics, which helps businesses predict demand, identify hazards, and streamline operations. BDA helps prevent stockouts, minimise excess inventory, and optimise inventory levels, reducing costs and raising customer satisfaction. It does this by examining data such as stock levels, demand trends, and lead times. BDA supports contract and supplier relationship management through risk identification, performance monitoring, and compliance assurance (Biazzin & Carvalho, 2019). BDA facilitates spend analytics, which helps procurement departments reduce costs, strengthen contract talks, and improve supplier performance by finding areas of overspending, grouping, and negotiating advantageous terms (Lutfi et al., 2022). BDA helps businesses assess the performance of their suppliers by examining quality, delivery, and pricing data to find high-performing ones and improve underperforming ones (Queiroz & Telles, 2018; Lee & Mangalaraj, 2022). Sosa and Paciello (2021) claim that BDA will make data-driven decisions possible by highlighting trends and insightful information from enormous data sets that will have a big impact on the procurement process.

Big Data Analytics and Supply Chain Management

BDA can greatly improve SCM and encourage further integration throughout the chain (Arunachalam et al., 2018). Big Data Supply Chain Analytics (BDSCA) has a significant direct impact on the SCs (Mubarik et al., 2019). In addition to supporting operational planning and SC operations, BDA helps businesses with strategic product design, sourcing, and SC network design (Wang et al., 2016). Mageto (2021) highlights that massive amounts of data are generated in a BD environment and shared in real-time with SC partners from many sources. BDA enables industrial SCs to embrace smart manufacturing and smart logistics principles (Mageto, 2021). Raman et al. (2018) posit that BD may also aid in bridging the gap between the supply and demand chains. Thus, BDA plays a crucial role in improving SC visibility, flexibility, and resilience. Implementing BDA may increase productivity, visibility, efficiency, and teamwork in addition to enhancing communications with SC members (Bahrami et al., 2022).

BDA improves SCM through increasing visibility, and SC visibility is recognised as one of the most crucial organisational characteristics to boost SCM and strengthen resilience (Gunasekaran et al., 2016). Bag et al. (2020) establish that operational success in SC is greatly influenced by its capacity to handle optimisation concerns pertaining to resource planning and utilisation, and BDA is a valuable solution for these issues. BD technologies are being used to increase SC visibility and aid decision-making in order to mitigate risks and disruptions in supply networks (Levelling et al., 2014). Tantawy et al. (2021) found that merchants can leverage BDA technologies to boost SC visibility, which will enhance product availability, lower fulfilment costs, and raise customer satisfaction. BDA is necessary to lower risks, streamline procedures, and improve SC visibility.

BDA improves supplier-buyer collaboration by integration and increasing customer-supplier visibility (Patrucco et al., 2022). Al-Khatib (2023) observed that BDA positively and significantly impacts SC visibility. BDA may be able to handle this complexity by providing visibility into numerous SC constituents. Chen et al. (2020) claim that BDA would make it easier for companies to successfully apply the principles of SC flexibility. Bahrami et al. (2022) assert that the primary drivers of SC flexibility are three critical components: BDA relationship expertise, BDA technology management capability, and BDA business understanding. Dubey (2019) establishes that competitive advantage and SC flexibility are positively impacted by the ability to implement BDA. SC flexibility is crucial for improving organisational performance because it functions as a mediator between BDA, organisational flexibility, and organisational performance (Aljumah, 2022). Handanga et al. (2021) found that BDA can strengthen SC partnerships by offering insights about supplier performance, customer demand, and other variables that impact SC flexibility. Dubey (2019) reveals that BDA capabilities have a significant and positive impact on SC flexibility and competitive advantage. Thekkoote (2022) discovered a positive correlation between the BDDSC model and the SC performance metrics and customer satisfaction.

BDA helps SC experts optimise distribution routes, enhancing the SC flexibility by enabling companies to respond quickly to shifts in supply or demand (Stefanovic, 2021). Sakib (2021) affirms that BDA can help with more precise demand forecasting, giving SC greater flexibility by enabling companies to modify their production and inventory levels in response to variations in demand. Businesses use BDA to boost the flexibility of SCs and simplify processes, save expenses, and respond promptly to changing market conditions. Businesses like Walmart, Amazon, Procter & Gamble, UPS, Ford, and Procter & Gamble can gain a competitive advantage and improve their ability to compete in today's fast-paced business environment by implementing BDA (Stefanovic, 2021; Sazu & Jahan, 2022; Handanga et al., 2021; Sakib, 2021). BDA is used to improve performance and decision-making for a range of SC operations by identifying disruptions and other SC concerns (Mubarik et al., 2019; Narwane et al., 2021). Singh (2019) discovered that BDA functions as a mediator between SC disruption events and the capacity of an organisation to build risk adaptation. Businesses enhance the capability to manage SC risks with the help of BDA. Companies that adopt BDA are more proficient at managing SC risk and utilising internal company data. BDA facilitates the management of complexity and enhances decision-making for SC risk and disruption management (Levelling et al., 2014; Tantawy et al., 2021; de Assis Santos & Marques, 2022).

BDA acts as a mediator between the organisational capacity to build risk resilience to SC disruption events and the impact of information technology infrastructure competency (Singh, 2019). Lohmer et al. (2020) claim that adopting BDA improves SC resilience by making strategy execution simpler, boosting resilience to disruptions, and successfully managing risks. Shah et al. (2023) and Park and Singh (2023) confirm that BDA helps companies to develop a risk profile that guides decision-makers and risk managers to make decisions more rapidly and efficiently, reducing SC risks and enhancing its resilience. Papadopoulos et al. (2017) assert that BDA presents a multitude of chances for accelerating recovery procedures in the case of SC disruptions. The detrimental effects of SC disruption events are lessened with the aid of BDA capabilities (Singh, 2019). As a result, BDA is now the resilience driver of the SC network (Papadopoulos et al. 2017). BDA enhances SC performance by lowering disruption impacts, increasing innovation, and strengthening disaster resilience (Li et al., 2023). Li (2022) found that BDA increases flexibility and resilience in enterprises by assisting in risk prediction and backup plan creation. Singh (2019) established that businesses that use BDA abilities are better able to manage SC risk and make better use of internal firm knowledge.

Nonetheless, Roberta Pereira et al. (2014) found that procurement plays a critical role in recognising and resolving intra- and inter-organisational challenges that impair SC resilience. Procurement processes can aid in the creation of SC resilience by facilitating the improvement of SC resilience (Deloitte, 2022). Harju et al. (2023) assert that digitising the procurement process can reduce SC uncertainty and enhance information processing skills. da Silva et al. (2016) claim that procurement function fosters connections, risk management, and continuous improvement, all of which increase SC resilience. Ghadafi et al. (2023) discovered that SC resilience and visibility are tightly connected. Raising risk awareness and offering visibility, flexibility, velocity, collaboration, and traceability systems contribute to increased resilience. Mandal (2017) found that a

SC can develop resilience with the aid of many forms of visibility, including supply, market, and demand data. Zhang and Zhao (2019) found that BDA strengthens SC resilience by raising visibility. Siagian et al. (2021) established that SC flexibility enables businesses to react quickly to SC turbulences. Sabahi and Parast (2020) observed that innovative companies tend to be more resilient to shocks related to SCs. Innovation enhances resilience-boosting abilities like flexibility, agility, and knowledge sharing.

METHOD OF DATA COLLECTION AND ANALYSIS

Research philosophy is the collection of beliefs that researchers have about the nature of knowledge and the ways to acquire it. Research philosophy is defined as a set of concepts, ideas, and presumptions that direct the research process (Guba & Lincoln, 1994; Becker, 1996; Saunders et al., 2009). This study adopted an epistemological approach based on the study of knowledge to ascertain the relevant data and draw conclusions. Ryan (2018), Sadiq (2021), and Noordin (2011) state that two epistemological stances that inform research techniques and analysis are positivism and interpretivism. Alakwe (2017) claims that positivism promotes the use of empirical data and the scientific method in the pursuit of knowledge. While interpretivism believes that there is no objective fact or truth in the social world and that knowledge and interpretation of reality are the products of social constructs (Noordin, 2011; Alharahsheh & Pius, 2020; Ikram & Kenayathulla, 2022).

The study used positivism to give the most thorough explanation of the objective reality. This approach studies what it takes to be a static reality using quantitative analysis in order to derive general rules that define social behaviour. Measurement and evaluation of the causal linkages between discrete variables are fundamental to an a priori theory-based, logical, reductionistic, and deterministic framework (Yilmaz, 2013). On that note, the study employed primary data to conduct an empirical investigation of the significance of BDA in the procurement process and SCM in the NMI. Thus, explanatory survey research was used for data collection, analysis, and interpretation. This study focused on the decision to survey professionals in the field. The findings of the study buttressed the narrative of current practices in the industry.

The questionnaire used for data collection was developed using the body of existing literature on BDA, procurement, and SCM. The data were gathered using a structured questionnaire that allowed for the identification of extreme data, the capture of causal relationships, and the provision of generalisable remarks regarding the research context (Pinsonneault & Kraemer, 1993; Gable, 1994). A copy of the questionnaire was sent to industry experts in the Nigerian manufacturing sector using an online Google form. This was accomplished by providing a link to the online survey questionnaire to industry professionals in logistics and supply chain management, members of the Chartered Institute of Logistics and Supply Chain Management, and other relevant institutes in Nigeria. The online survey questionnaire was divided into three sections. This includes a consent letter, demographics, and closed-ended questions on BDA, procurement, and SCM. Participants rate their agreement or disagreement with specific assertions. These closed-ended questions permit less room for individual interpretation and answer diversity and reduce response bias. The 20-item questionnaire on a five-point Likert scale that ranged from 1 being "strongly disagree" to 5 being "strongly agree" reflects the opinions of the professionals. The participants were informed about the study topic. As a result, after receiving a sufficient amount of responses, the information was verified to ascertain its level of accuracy.

The study could not obtain data from the entire population; it was able to address this limitation by drawing generalisations from samples of the population. A representative sample was chosen from a broader population using sampling techniques. This guarantees that the results can be applied to the target population (Rahman et al., 2022). Representative samples are crucial for data collection since they ensure that participants are relevant to the topic while also reducing bias and inaccuracy (Saunders and Townsend, 2016). The study considered one of the qualities of an objective scientific study when study participants were selected to avoid sample bias. A multiple case study approach was chosen to assess the relationships mentioned for the observed factors. As a result, information was gathered from experts in the field of logistics and supply chain management, members of the Chartered Institute of Logistics and Supply Chain Management, and members of other relevant institutes in Nigeria. These experts oversee the execution of several supply chain and procurement duties at listed Nigerian manufacturing companies and other players in the industry. This enabled the study to broadly focus on the collection of varied viewpoints that are relevant to the expertise and operational capacities of numerous companies. For the purposes of the study, the opinion of the experts served as a true sectoral opinion.

The study examined the significance of the linear relationship using linear curve estimation (LCE). This led to the adoption of linear equation models to estimate the relationships between the variables. A linear curve estimation entails assessment of the relationships between variables using observable data (Williams et al., 2018). Thus, the usage of linear equations to illustrate the associations between variables. These equations can be used to estimate the coefficients that describe the significance and direction of the associations. Therefore, the relationships between the variables in the model are estimated using linear equations. These steps assisted the study in obtaining credible and reliable results (Razaghi & Shokouhyar, 2021). The variables in the estimated models are big data analytics (BDA), procurement processes (PP), supply chain management (SCM), supply chain visibility (SCV), supply chain flexibility (SCF), and supply chain resilience (SCR). The linear curve estimation model to be adopted in the study is specified below.

$PP_i = \beta_o + \beta_1 BDA_{i1} + \mu_i$ ……………………………………………….……….. (1)

$SCM_i = \beta_o + \beta_1 BDA_1 + \mu_i$ …………………………………………..………. (2)

$SCR_i = \beta_o + \beta_1 EPP_1 + \mu_i$ ………………...…………………………………..… (3)

$SCR_i = \beta_o + \beta_1 SCV_1 + \mu_i$ ………………………………………………..……... (4)

$SCR_i = \beta_o + \beta_1 SCF_1 + \mu_i$ ……………………………………….……..……... (5)

Where:

PP_i = Dependent Variable Measured by Procurement Process

SCM_i = Dependent Variable Measured by Supply Chain Management

SCR_i = Dependent Variable Measured by Supply Chain Resilience

BDA_1 = Independent Variables Measured by Big Data Analytics

EPP_1 = Independent Variables Measured by Efficient Procurement Process

SCV_i = Independent Variable Measured by Supply Chain Visibility

SCF_i = Independent Variable Measured by Supply Chain Flexibility

β_o = Intercept of the Estimation Model

β_1 = Coefficient of determination Associated with Independent Variable

μ = Random Error Associated with the Estimation Model.

The study used exploratory factor analysis (EFA) to determine the underlying structure of a set of variables. This assisted the study in determining the fundamental causes of the patterns of relationships between the variables (Costello & Osborne, 2005). This approach helped in determining the most significant components that contribute to the construct being measured as well as underlying factors or dimensions that explain the interactions among a set of observable variables (Duchovičová & Tomšik, 2018). Reliability and validity tests are used in this study to assess the responses of various participants as well as their credibility, consistency, and repeatability. Cronbach's alpha was used to assess internal consistency and reliability for each scale. Cronbach's alpha is a trustworthy metric for evaluating internal consistency, measuring instrument consistency, and underlying concept capture (Peterson, 1994; Tavakol & Dennick, 2011). Higher values of the Cronbach's alpha index, which goes from 0 to 1, indicate better internal consistency. A value of 0.7 or above is typically

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regarded as appropriate for research purposes (Peterson, 1994; Chin, 1998; Tavakol & Dennick, 2011). To protect the survey participants and uphold ethical consideration, the study ensured that the data were managed in compliance with data privacy and used only for this study.

Data Analysis

Big Data Analytics and Procurement Process

The results of the regression estimation on the significance of BDA on the procurement process are presented in Table 1. The results showed that BDA had a positive and significant influence on the procurement process. The result of the intercept estimate is statistically significant at the 5% level with a coefficient value of 1.502, and the estimated standard deviations of the pertinent sample distributions showed a value of 0.264. This suggested that when the model parameter remained constant, the procurement process grew by 1.50%. The regression analysis produced a coefficient of 0.653, or the slope estimate for BDA, when considering the impact of BDA on the procurement process of the Nigerian manufacturing industry. This outcome is statistically significant at the 5% level. This indicates that a 1% increase in the BDA capabilities in the industry led to a 0.65% rise in the procurement process.

Table 1 Big Data Analytics and Procurement Process

	Coefficients	Std. Error	R Square	Adjusted R Square
Intercept	1.502***	0.264		
BDA	0.653***	0.064	0.444	0.440

Source: Linear Curve Estimation using SPSS

Note: (1) Number of observation is 133

(2) PP = Procurement Process, BDA = Big Data Analytics

***Significant at 5%.

The estimated standard deviations of the relevant sample distributions or standard errors have a value of 0.064. If the study repeats the entire experiment multiple times, the estimate for the coefficient of BDA, which is 0.653 in this case, will vary with a standard deviation of about 0.064 around an unknown value. This is an indication of the scope of the variability by the standard error of 0.064 for the predictor variable. This implies a stronger and more reliable association between the predictor and responder variables, as seen by the estimated coefficients being more accurate. The summary of the regression model showed that R square, which determines how well a regression model fits the data, has a value of 0.444. This indicates that 44.4% of the variation in the procurement process was explained by the estimating model. This fluctuation was adjusted to 40% as revealed in the adjusted R-Square, which appears that the study model has a good fit. This result is consistent with the study conducted by Kumar and Chakraborty (2022), which found that BDA enhances procurement through the provision of supplier performance insights, the identification of cost-saving options, and increased SC efficiency.

Big Data Analytics and Supply Chain Management

The results of the regression estimation in Table 2 evaluate the impact of BDA on supply chain management. The findings demonstrated that BDA has a positive and significant impact on SCM. At the 5% level, the intercept coefficient value of 1.967 indicated statistical significance. It found that the relevant sample estimated standard error of the distributions is 0.263. This implied that SCM rose by 1.97% when the model parameter remained constant. The regression estimation on the impact of BDA on the supply chain management of the Nigerian manufacturing industry recorded a coefficient of 0.484. This result is positively and statistically significant at the 5% level of significance. This demonstrates that in the Nigerian

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manufacturing industry, a 1% increase in BDA capabilities resulted in a 0.48% rise in SCM.

Table 2 Big Data Analytics and Supply Chain Management

	Coefficients	Std. Error	R Square	Adjusted R Square
Intercept	1.967***	0.263		
BDA	0.484***	0.063	0.308	0.303

Source: Linear Curve Estimation using SPSS

Note: (1) Number of observation is 133

(2) SCR = Supply Chain Management, BDA = Big Data Analytics

***Significant at 5%.

The standard errors with a value of 0.063 display the estimated standard deviations of the relevant sample distributions. The estimated BDA coefficient, which is 0.484, will fluctuate with an approximate standard deviation of 0.063 around an unknown value if the full experiment is repeated in the study. This result illustrates the predictor degree of variability for the variable. Hence, the estimated coefficients are probably more trustworthy, suggesting a stronger and more consistent relationship between the response variable and the predictor variable. The outcome of the R square revealed 0.308 in the regression model summary. The result suggests that the study model fits the data well, as it shows that the estimated model explained 30.8% of the variation in SCM. The outcome of the adjusted R-Square showed 30.3% variation in the explained response variable. The outcome in this regression estimation is consistent with other existing studies such as Singh (2019), Li (2022), Li et al. (2023), and Lohmer et al. (2020), among others that recorded positive and significant influence of BDA on SCM.

Supply Chain Resilience and Efficient Procurement Process

The impact of an effective procurement process on SC resilience was revealed in the results of the regression estimation displayed in Table 3. The results showed that EPP has a positive and significant impact on SC resilience. The coefficient value of the intercept estimate is 1.420 and statistically significant at the 5% level. Similarly, the estimated standard error of the relevant sample distributions for the intercept slope is 0.241. This is an indication that SC resilience increased by 1.42% when the model parameter was constant. The EPP slope estimate was determined by the regression estimations, which yielded a coefficient of 0.606. This outcome is statistically significant at the 5% level of significance. This demonstrates that a 1% rise in EPP raised SC resilience by 0.61% in the Nigerian manufacturing industry. The estimated standard deviations of the relevant sample distributions are displayed in the standard errors, which have a value of 0.057.

Table 3 Supply Chain Resilience and Efficient Procurement Process

	Coefficients	Std. Error	R Square	Adjusted R Square
Intercept	1.420***	0.241		
EPP	0.606***	0.057	0.462	0.458

Source: Linear Curve Estimation using SPSS

Note: (1) Number of observation is 133

(2) SCR = Supply Chain Resilience, EPP = Efficient Procurement Process

***Significant at 5%.

This signifies that if the complete experiment is repeated in the study, the estimated EPP coefficient will fluctuate by 0.057 with a standard deviation around the mean for an unknown value. The degree of variability in the predictor variable is demonstrated by this result. Consequently, the predicted coefficients are likely to be more reliable, suggesting a stronger and more accurate relationship between the response variable and the predictor variable. The regression model summary revealed that the R square recorded the value of 0.462, which is an indication that the estimated model accounted for 46.2% of the variation in SC resilience. The adjusted R-Square result reported 45.8% variation in the explained response variable, demonstrating a good fit model. This result supported the finding of Roberta Pereira et al. (2014) that procurement significantly impacts SC resilience.

Supply Chain Resilience and Supply Chain Visibility

The findings of the regression estimation in Table 4 evaluate the impact of supply chain visibility on the supply chain resilience of the Nigerian manufacturing sector. According to the findings, SC visibility had a positive and significant impact on SC resilience. The result of 1.626 for the intercept estimate is statistically significant at the 5% level. The estimated standard error of the relevant sample distributions is 0.214. This suggests that maintaining a consistent value for a model parameter improves SC resilience by 1.63%.

Table 4: Supply Chain Resilience and Supply Chain Visibility

	Coefficients	Std. Error	R Square	Adjusted R Square
Intercept	1.626***	0.214		
VSC	0.577***	0.052	0.480	0.476

Source: Linear Curve Estimation using SPSS

Note: (1) Number of observation is 133

(2) SCR = Supply Chain Resilience, SCV = Supply Chain Visibility

***Significant at 5%.

The regression estimates revealed a coefficient of 0.577, which is the slope estimate for SC visibility. This result is positively and statistically significant at the 5% level of significance. This is an indication that SC resilience increased by 0.58% for every 1% increase in SC visibility. The standard errors, with a value of 0.052, display the estimated standard deviations of the relevant sample distributions. The predicted SC visibility coefficient will vary with a standard deviation of approximately 0.052 for an unknown value if the full experiment is replicated in the study. The predictor variability is demonstrated by this result, suggesting a stronger and more accurate association between the predictor and response variables; as a result, the predicted coefficients are probably more dependable. The result of the R square is 0.480 in the summary of the regression model. It demonstrated that the study model fits the data well because it explained 48% of the variation in SC resilience. The result of adjusted R-Square revealed 47.6% variation in the explained response variable. Brandon-Jones et al. (2014) found that SC visibility capabilities also increase SC robustness and resilience, which is consistent with this finding.

Supply Chain Resilience and Supply Chain Flexibility

Table 5 presents the results of the regression estimation, which examines the influence of supply chain flexibility on the resilience of the supply chain in the Nigerian manufacturing industry. The results showed that the flexibility of SC positively and significantly influenced the resilience of SC. The result of 1.037 for the intercept estimate is statistically significant at the 5% level. The estimate of the intercept standard error is 0.290 for the slope of relevant sample distributions. This result indicates a 1.04% improvement in SC resilience when a model parameter was held constant. The coefficient of the estimate for SC flexibility is 0.704, and this is statistically significant at the 5% level. This outcome implies that a 1% increase in SC flexibility increased SC resilience by 0.70.4%. The estimated standard deviations of the relevant sample distributions are represented by the standard errors, which have a value of 0.070. In this case, the estimated SC flexibility will vary with an uncertainty of approximately 0.070 if the full experiment is repeated in the study. This result signifies an accurate and strong correlation between the predictor and response variables by illuminating the variability predictor variable. Therefore, it is likely that the projected coefficients have more reliability.

Table 5: Supply Chain Resilience and Supply Chain Flexibility

	Coefficients	Std. Error	R Square	Adjusted R Square
Intercept	1.037***	0.290		
SCF	0.704***	0.070	0.438	0.434

Source: Linear Curve Estimation using SPSS

Note: (1) Number of observation is 133

(2) SCR = Supply Chain Resilience, SCF = Supply Chain Flexibility

***Significant at 5%.

The outcome of the R square in the regression model summary depicted 0.438, and this is an indication that 43.8% of the variation in SC resilience was explained by the study model, indicating that the model was a good fit. The adjusted R-Square showed that 43.4% of the deviation in the response variable was explained by the estimated model. This result aligns with the findings of Siagian et al. (2021), who found that the flexibility of the SC makes firms robust by allowing them to respond swiftly to disruptions in the SC.

Cronbach's Alpha and Exploratory Factor Analysis

Cronbach's alpha was employed in the study to evaluate the consistency of responses to different scale items. The coefficient results of the scale of the Cronbach's alpha are greater than 0.7, signifying that all of the elements exhibited strong reliability. This proves the study met the internal consistency and reliability requirements of the survey. Similar to the factor loading, the pattern matrix results also averaged greater than 0.7, indicating that the data are significant enough to exhibit convergent validity. Since there was no cross-loading among the factors and the factor correlation matrix result indicated that there is a relationship between the factors of greater than 0.7, the results for the diagnostic of discriminant validity are good. The KMO and Bartlett's test illustrated the sample adequacy measure, producing excellent results that are statistically significant at the 5% level. There is proof that there is no problem with the communalities, as none of the retrieved values for the communalities' extraction are less than 0.3. The cumulative extraction sums of squared loadings recorded greater than 60% value. The chi-square goodness of fit result for the test indicated a strong fit, and this is statistically significant at the 5% level.

IMPLICATIONS OF THE FINDINGS

Utilising BDA capabilities offered industry companies a competitive advantage and aid decision-making. BDA reduced expenses and increased efficiency by accurately forecasting fluctuations in raw material prices and optimising inventory levels in the industrial sector (Biazzin & Carvalho, 2019; Li et al., 2020). Predictive analytics solutions in procurement allowed manufacturing to anticipate demand, spot risks, and optimise workflows. BDA also helped organisations in the industry manage contracts and supplier relationships by detecting risks, monitoring performance, and guaranteeing compliance (Biazzin & Carvalho, 2019; Queiroz & Telles, 2018). BDA had helped procurement by monitoring spending trends, spotting areas of excessive spending, consolidating, and negotiating better terms with suppliers. It also assisted in risk management by spotting hazards and identifying suppliers that might experience political or commercial instability (Lee & Mangalaraj, 2022; Lutfi et al., 2022). Thus, BDA had a big impact on the procurement procedure in the

Nigerian manufacturing industry.

BDA deployment in the industrial sector has increased productivity, efficiency, visibility, and teamwork, all of which contribute to increased SC flexibility by facilitating better communication between participants. BDA increases SC visibility, which is essential for organisational resilience and resource planning in SCM (Gunasekaran et al., 2016; Bag et al., 2020; Bahrami et al., 2022). Tantawy et al. (2021) observed that BDA capabilities increased product availability, decreased fulfilment costs, and raised customer satisfaction, which boosted merchant exposure of SC. BDA improves supplier-buyer cooperation, lowers risks, and streamlines procedures. It enhances SC performance by providing multi-component visibility (Patrucco et al., 2022; Al-Khatib, 2023). Chen et al. (2020) discovered that BDA can assist organisations in more successfully putting SC flexibility ideas into practice. Competitive advantage and SC flexibility are significantly impacted by BDA.

SC flexibility serves as a mediator between BDA, organisational flexibility, and performance (Bahrami et al., 2022; Aljumah, 2022; Dubey, 2019). Thekkoote (2022) found that SC analytics positively correlate with SC performance metrics and customer satisfaction when BDA capabilities are adopted. BDA assists SC specialists in optimising distribution routes, enhancing adaptability by facilitating prompt responses from enterprises to shifts in supply or demand, and supporting precise demand projections. Because of this, businesses can swiftly move to different providers, increasing the flexibility of SC. It is apparent that many businesses employ BDA to achieve a competitive edge in the fast-paced business environment by streamlining operations, reducing expenses, and responding swiftly to changing market conditions (Stefanovic, 2021; Sazu & Jahan, 2022; Cheng et al., 2022; Handanga et al., 2021; Sakib, 2021).

BDA improves performance and decision-making in a variety of SC tasks by identifying and resolving SC difficulties. It improves decision-making and risk management capacity by serving as a mediator between an organisation's risk adaptation and SC disruption situations (Mubarik et al., 2019; Singh, 2019; Narwane et al., 2021). By enhancing information technology infrastructure competency and risk resilience, BDA implementation strengthens the ability of resilient SCs to withstand shocks and bounce back. It helps companies to increase their capacity for innovation and resilience to disasters, which boosts productivity and reduces SC risks. Organisations in the manufacturing sector need BDA capability to ensure effective SCM and to manage SC resilience (Tantawy et al., 2021; Santos & Marques, 2022; Shah et al., 2023; Santos & Marques, 2022; Park & Singh, 2023). BDA provides SCs with the chance to prepare for recovery more quickly and with greater resilience. It lessens the negative effects of disruption situations and assists organisations in avoiding unplanned outages. BDA improves SC performance through lowering disruptive effects, increasing resilience to disasters and innovation, and increasing efficiency (Papadopoulos et al., 2017; Singh, 2019; Li et al., 2023). Thus, BDA plays a critical role in risk prediction, backup planning, SC resilience management, and enhancing internal firm knowledge for effective SCM in NMI.

Procurement has a significant impact on SC resilience by recognising and resolving intra- and inter-organisational problems. Procurement may strengthen resilience by adjusting to technological advancements and market trends, digitising the process, cultivating connections, controlling risk, and advancing continually (Roberta Pereira et al., 2014; da Silva et al., 2016; Harju et al., 2023). Traceability systems boost resilience by promoting risk awareness, adaptability, visibility, and cooperation (Ghadafi et al., 2023). Developing SC system resilience requires SC visibility. It can be improved by means of different kinds of visibility, information sharing, integrated logistics, business-to-business collaboration, and flexibility (Zhang & Zhao, 2019; Scholten & Schilder, 2015; Mandal et al., 2017). SC resilience is eventually increased via innovation, which enhances competencies like information exchange, and flexibility allows SC to respond quickly to disturbances and market fluctuations. Businesses with flexibility are more robust to unanticipated obstacles because they can better handle disruptions (Siagian et al., 2021; Sabahi & Parast, 2020). Effective procurement processes, supply chain visibility, and supply chain flexibility are critical for managing SC resilience through manufacturing industry preparedness to manage unforeseen events, react swiftly, and resume operations after disruptions.

CONCLUSIONS AND PRACTICAL POLICY IMPLICATIONS

The study concludes that big data analytics has a significant impact on procurement and supply chain management in the Nigerian manufacturing industry. Companies in NMI use BDA to process a range of data to achieve efficient operations, make smarter decisions, and spot trends in customer behaviour. This process transforms data into actionable knowledge to improve procurement processes and supply chain management, in turn boosting competitive advantage, customer satisfaction, and brand loyalty. There is evidence of the interconnectivity among the complex structures in SCM, and the study concluded that efficient procurement processes, SC visibility, and SC flexibility contributed to SC resilience in NMI. The industry used SC analytics to remain resilient in the disruptions of SC in the volatile market through efficient procurement processes, SC visibility, and SC flexibility. In line with knowledge management theory and competitive advantage theory, this study supports the notion that gathering, analysing, and applying valuable insights are essential for optimal operations and competition in the industry.

The stakeholders in NMI need to adopt BDA capabilities to improve effective procurement processes. This will be achieved by putting e-procurement into practice, utilising BDA tools, following the protocols, managing contracts well, being transparent, and encouraging healthy competition. Smart contracts will remove the need for middlemen and manual intervention in NMI by automating procurement processes.

The regulators in the industry need to implement blockchain technology to increase SC visibility through transparency, traceability, efficiency, and security. The industry needs a decentralised ledger for interactions and transactions, guarding against data manipulation, fraud, and corruption. This will allow goods and services in NMI to be traced in real time across SC, verifying their legitimacy and compliance with regulations. Blockchain will reduce the need for human verification and boost efficiency in NMI by expediting supplier qualification through the storage of data, credentials, and certifications. Blockchain's cryptographic technology will ensure the security and integrity of data in NMI.

Stakeholders must deploy RFID and IoT technologies in a number of SCM-related areas in NMI. Businesses will have access to real-time data, spot bottlenecks, streamline workflows, and react fast to supply or demand fluctuations by deploying sensors and trackers. Using standardised IoT technology lowers costs, prevents vendor lock-in, and guarantees interoperable devices. These automated procedures will boost SC efficiency, improve customer service, decrease waste and manual labour, and streamline inventory levels.

The stakeholders need robotics in several areas of SC operations in NMI. Robotics will dramatically reduce interruptions in SCs by automating monotonous jobs, boosting accuracy, speeding up operations, improving safety, gathering and analysing data, and enabling flexibility and adaptability. This technology will shorten lead times and lower insurance costs while decreasing the need for human labour and increasing efficiency and mistake reduction. It will also improve the ability of the organisation to react to and recover from disturbances, which will increase SC resilience in NMI.

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