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Big Data Analytics and market competitiveness of selected firms in Lagos State, Nigeria

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Abstract

Purpose: This study specifically evaluates the effect of Intangible Big Data Analytics Resources (IBDAR) and Tangible Big Data Analytics Resources (TBDAR) on a firm's market competitiveness in manufacturing firms. The authors used RBV as the main theoretical framework to investigate this.

Research methodology: This study used a survey research design. The study employed a non-probability sample and a final sample of seventy-two employees selected from manufacturing firms in Lagos State, Nigeria.

Results: The hypotheses were tested using multiple linear regressions. The empirical results showed that the organizational use of TBDAR has a significant effect on Market Competitiveness (MCOM), and that the organizational use of IBDAR has a significant effect on MCOM.

Limitations: First, the sample is restricted to only the Nigerian setting; to draw broader and deeper implications, it could be useful to take diverse samples from different contexts and sectors. Second, this study does not utilize the PLS-SEM technique to model mediators and moderators.

Contribution: This study has significant policy implications for practitioners and is an original study based on primary data from Nigerian manufacturing firms.

Keywords: *Big Data, Big Data Analytics, Market Competitiveness, Tangible Big Data Analytics Resources, Intangible Big Data Analytics Resources*

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1. Introduction

Corporate internationalization and digitization have produced a vast amount of data that firms must utilize to remain competitive. Big Data (BD) are heterogeneous datasets that comprise collections of various informational amounts and types (Pauleen & Wang, 2017). It is a collection of massive electronic data, that is, structured and unstructured, whose contents cannot be captured, managed, and processed by conventional software tools within a certain period (Li, 2022). BD is very large and complex to deal with using traditional data-processing application software. Thus, the current informational environment requires the implementation of BD techniques to analyze such voluminous data. New data-processing models need to be developed to stimulate information that can be useful for decision-making. Using BD, managers can keep an eye on all organizational functions, resources, production units, and supply chains (Khan & Vorley, 2017). Big Data Analytics (BDA) is a new trend that has the potential to revolutionize how businesses manage and improve company performance. To deal with this high level of uncertainty, investigate and scan the market, and assess risks, BDA can offer real-time, detailed, and multisource information (Dam, Le Dinh, & Menvielle, 2019; Gnizy, 2019).

BDA is a complex process of examining BD to uncover information such as hidden patterns, correlations, market trends, and customer preferences that can help organizations make informed business decisions. BDA helps organizations make data-driven decisions and increases operational effectiveness. BDA's influence on business has grown significantly during the last few years (Alotaibi, Alotibi, & Zraqat, 2021). It has attracted major investment from many international firms (Alrashidi, Almutairi, & Zraqat, 2022). Firms use BDA to identify business risks and inefficiencies in systems and processes and take the necessary remedial action. BDA enables managers to monitor and have knowledge of their organizations, competitors, and clients (Cappellesso & Thomé, 2019; Zhang, Wang, & Pauleen, 2017). BDA enables managers to understand customer behavior, trends, needs, and complaints. It also helps managers assess customers at the individual and aggregate levels, which is often fluid in the 21st century (Aljumah, Nuseir, & Alam, 2021).

The authors establish a link between BDA and a firm's market competitiveness. For instance, Brewis, Dibb, and Meadows (2023) found that BDA from expanding market knowledge can provide firms with strategic insights that can increase an organization's profitability and competitiveness. Mikalef et al.Mikalef, Pappas, Krogstie, and Giannakos (2018) pointed out that BDA impacts an organization's marketing strategy from its capacity to respond quickly to the creation of new strategies. This follows from its role in 'market sensing, which accurately reveals market segments, customer demands, and rival offers (Brynjolfsson, Hitt, & Kim, 2011; Slater & Narver, 2000; Teece, 2018). According to Brynjolfsson et al. (2011), this additional knowledge can be used to support improved business procedures and improved performance levels.

Similarly, Santoro, Fiano, Bertoldi, and Ciampi (2019) find that BDA leads to the creation of dynamic capacities. Thus, BDA can enhance a firm's competitiveness by improving customer relationships, improving operational risk management, and enhancing efficiency and performance (Bresciani, Ferraris, & Del Giudice, 2018; Brynjolfsson et al., 2011; Mikalef, Boura, Lekakos, & Krogstie, 2019). BDA's limitless access to detailed information enables managers to become better informed about the status of various business processes, including the supply chain, employee productivity, internal operations, and consumer behavior patterns (Bresciani et al., 2018; Dubey, Gunasekaran, & Childe, 2018). Thus, organizations that adopt BDA in their business strategies have a variety of benefits.

The manufacturing sector is in a state of flux and faces challenges as a result of rapid digitization, which calls for efficient marketing techniques to engage new clients. Many firms increasingly rely on BDA to match their rivalry. In many industries, both long-established firms and newcomers, data-driven tactics are employed to innovate, compete, and enhance value (McGuire, Manyika, Chui, Manyika, & Chui, 2012). For instance, in the manufacturing context, BDA allows a narrower segmentation of customers and, therefore, more precisely tailored products or services (De Mauro, Greco, Grimaldi, & Ritala, 2018). It also aids in substantially improving decision-making, minimising risks, and unearthing valuable insights that would otherwise remain hidden (Aljumah et al., 2021; McGuire et al., 2012; Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020). Thus, BDA's ability to analyze sizable pools of data to find patterns and make better decisions serves as a foundation for manufacturing firms' growth and competitiveness, increases productivity, and adds significantly to the global economy by lowering waste and raising the calibre of goods and services (McGuire et al., 2012).

Current research on the connection between BDA and a firm's market competitiveness is crucial. This study builds on earlier studies to establish the effect of BDA on a firm's market competitiveness. The growing amount of information available to manufacturing firms requires them to implement advanced techniques to better analyze the data. BDA is crucial to a firm's sustainable market competitiveness. Second, while there have been fewer studies conducted in developing countries, the effect of BDA on competitiveness has primarily been studied in developed countries. Finally, most studies have been qualitative or theoretical (Cillo, Rialti, Del Giudice, & Usai, 2021; Santoro et al., 2019).

This study contributes to the literature by adding to the body of knowledge on BDA and a firm's market competitiveness in developing markets. The implementation of BDA is likely to have a substantial effect on the performance of manufacturing enterprises. Most empirical research conducted in developed nations cannot be extrapolated to the Nigerian market, necessitating further explanation of the link. Against this backdrop, this study examines the effects of BDA on a firm's market competitiveness. The specific objectives of this study are as follows:

1. To ascertain the effect of the organizational use of intangible BDAR on market competitiveness.
2. To examine the effect of organizational use of tangible BDAR on market competitiveness.

2. Literature Review

2.1. Conceptual Review

2.1.1. Big Data Analytics (BDA)

Authors define BD around three key dimensions: variety, volume and velocity, i.e., it constitutes data of different formats [variety]-both structured and unstructured, often challenges or exceeds an organisation's storage and processing capacity (comprising terabyte and petabytes of information) [volume], and which must be processed quickly (usually in milliseconds) for effective real-time decision making [velocity] (e.g., Krishnan (2013); Madden (2012); Manovich (2011); Russom (2011); Schroeck, Scockley, Smart, Romero-Morales, and Tufano (2012); Soares (2012)). This definition has been extended to include a fourth V-veracity, which focuses on issues such as data quality (Ellars, 2013; Hitzler & Janowicz, 2013). Veracity emphasizes the notion of "data as a resource" (Kambatla, Kollias, Kumar, & Grama, 2014) that can confer a competitive advantage to organizations (Brown, Chui, & Manyika, 2011; Brynjolfsson et al., 2011; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2010). BD differs from conventional data in terms of variability, velocity, volume, value, veracity, and visualization. BD refers to large and heterogeneous datasets that cannot be analysed using conventional statistical models (Ferraris, Mazzoleni, Devalle, & Couturier, 2019).

Big Data Analytics is described by the IAASB as the science and art of finding and analyzing patterns, deviations, and inconsistencies in data that underlie or are related to the subject matter through analysis, modelling, and visualization (ACCA, n.d.). BDA is the process of inspecting, cleaning, transforming, and modelling BD to discover and communicate useful information and patterns, suggest conclusions, and support decision-making (Cao, Chychyla, & Stewart, 2015). BDA translates all data into easily understood pre-structured forms or presentations for clients and produces programs customized to the risks specific to each client or supplies data directly into computerized procedures (ACCA, n.d.). Indeed, BDA is characterized as a "… holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions to gain actionable insights, create business value, and establish competitive advantage … " (Akter et al., 2019). BDA consists of a mix of competencies: infrastructural flexibility, managerial capabilities, and staff capabilities (Jeble, Kumari, Venkatesh, & Singh, 2020).

BDA improves the efficiency and effectiveness of organizational processes (Cao et al., 2015). To effectively utilize BDA, firms must use technologies that automate their decision-making processes continuously and autonomously. This is often done using a mix of cost-effective data collection, extraction and analysis tools and technology solutions referred collectively to as analytics (Chaudhuri, Dayal, & Narasayya, 2011; Chen, Chiang, & Storey, 2012; Russom, 2011; Turban, Sharda, Aronson, & King, 2008; Watson & Wixom, 2007). These technologies support real-time data retrieval, analysis, and fast-paced decision-making.

2.1.2. Benefits of BDA

BDA improves access to and manipulation of data and can assist managers in operational processes through the following:

a. increased operational understanding through a more thorough analysis of a client's data and the use of visual output, such as dashboard displays, rather than text or numerical information.
b. identification of risks associated with a client/customer segment, enabling further research and insight;
c. increased efficiency through the use of computer programs to perform very fast processing of large volumes of data and to provide analysis to managers on which to base their conclusions.
d. Information from BDA can be shared with clients and customers, adding value to the organizational function.

2.1.3. Firm's Market Competitiveness

The term 'market competitiveness' describes a company's capacity to successfully compete in its industry or market (Napier, Libert, & De Vries, 2020). This is simply a firm's ability to outperform its competitors in the marketplace. It gauges how successful a company can gain and keep customers, sell, and outperform its rivals. Market competitiveness is the capacity of an organization to draw in and hold onto customers/clients in comparison to its rivals. With recent technological advancements, organizations are looking for new methods to utilize the ensuing data to increase their market competitiveness (Napier et al., 2020). Several factors affect the market competitiveness. These factors include organizational (e.g., tangible and intangible resources) and macro-environmental factors (e.g., inflation).

Verhoef et al. (2021) encourage firms to follow a 3-stage approach to alter how they employ digital technology to generate valuable market insights: *firstly*, the digitisation of BD, can improve market intelligence and inspire adjustments to marketing strategy. *The second* is the digitalization of organizational processes (Autio, Nambisan, Thomas, & Wright, 2018). *Third*, an extensive organization-wide transformation fosters innovation and creates new business logic (Pagani & Pardo, 2017). This integrated approach can therefore lead to improved service quality or product offerings, which directly impacts a firm's market competitiveness (Yee, Yeung, Cheng, & Lee, 2013).

2.1.4. BDA and Firm's Market Competitiveness

Several authors have begun concentrating on how and to what extent BDA may help businesses gain a competitive edge (Amalina et al., 2019; Ren et al., 2019). Prior studies suggest that BDA can enhance the quality of decision processes (Kowalczyk & Buxmann, 2015); agility (Ashrafi, Ravasan, Trkman, & Afshari, 2019; Rialti, Marzi, Caputo, & Mayah, 2020); supply chain performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Shokouhyar, Seddigh, & Panahifar, 2020); innovation capabilities (Mikalef et al., 2019); and value creation (Seddon, Constantinidis, Tamm, & Dod, 2017). BDA can lead to organizational market competitiveness in several ways. For instance, the adoption of BDA requires personnel to obtain certain training and certification, which leads to better-skilled workers. In this manner, appropriate inferences can be made from the analysis. Through the use of these capabilities, organizations can gain a competitive advantage (Jeble et al., 2020).

Second, BDA allows managers to refocus their thinking by utilizing superior evidence to support their professional judgement and decision-making by visualizing it. According to Austin, Carpenter, Christ, and Nielson (2021), BDA provides managers with a strategic advantage in giving business-related insights to their clients. Zraqat (2020) opined that using BDA would enhance managerial decision-making and that such business intelligence tools would improve managers' capacity to offer quality judgment.

Third, BDA offers managers in-the-moment data analysis. Real-time data analysis has several advantages for managers. BDA uses automation and artificial intelligence to process data more quickly and in larger amounts, thereby providing managers with useful information. BDA can enhance human decision-making and, in some situations, even replace it, as it automates action in response to the created insight (Provost & Fawcett, 2013).

Finally, Popovič, Hackney, Tassabehji, and Castelli (2018) improved r to improve intsense-makingtsense-making in situations characterized by high complexity and velocity. Thus, BDA capabilities can improve an organization's capacity to identify emerging risks and opportunities (Mikalef et al., 2019; Rialti et al., 2020). Thus, firms that implement BDA have a far higher likelihood of creating new goods and services than those that lag (Ransbotham & Kiron, 2017).

Fifth, firms now utilize BDA to enable real-time process orchestration for logistics and supply chain activities (Schoenherr & Speier-Pero, 2015). Others make use of BDAs to advance towards the Industry 4.0 paradigm of smart manufacturing, which is based on cyber-physical systems that allow for quicker, more adaptable, and more efficient production of higher-quality items (Almada-Lobo, 2015). Thus, an organization's capacity to gather, prepare, and analyze BD may make a difference, particularly if it makes it challenging for others to replicate these procedures (Ferraris et al., 2019).

The BDA research stream has advanced more quickly owing to the possibility of performing creative, scalable, and dynamic data analyses (George, Osinga, Lavie, & Scott, 2016). BDA can also increase the agility of manufacturing companies, enabling them to enter the market with reduced prices and higher-quality goods and services (Gunasekaran, Yusuf, Adeleye, & Papadopoulos, 2018). BDA can provide information on customers and marketplaces that are geographically and culturally remote compared to conventional information systems by analyzing BD, which is often not available in firm-level datasets (Bertello, Ferraris, Bresciani, & De Bernardi, 2021).

2.1.5. Tangible and Intangible BDARs

Tangible BDARs can assist companies to build tailored products and services (Alyass, Turcotte, & Meyre, 2015), personalise their marketing strategies and target high-profit segments in customer management and service-providing operations, provide location-based and custom discounts (Grover, Chiang, Liang, & Zhang, 2018), make more precise and personalised recommendations for future purchases (Ngai, Gunasekaran, Wamba, Akter, & Dubey, 2017), and assist customers in resolving their issues using AI technologies (Orenga-Roglá & Chalmeta, 2016). Data, technology, and other basic resources are essential to BD's success of BD in terms of tangible resources. Tangible BDAR provides businesses with access to a wealth of information on consumers and markets, helping them better understand consumer preferences, behavior, and market trends. Firms can efficiently meet client requests by customizing their products, services, and marketing methods with the aid of this knowledge. Although data are a fundamental resource, it is also crucial for businesses to have an infrastructure that can store, share, and analyze BD.

Thus, consistent with Mikalef et al. (2019) classification, the following hypothesis is formulated:
H1: Organizational use of tangible BDAR has a significant impact on market competitiveness.

Most research on the benefits of BDAR for a company has shown an overall impact on performance indicators (Wamba et al., 2017). Thus, intangible BDAR benefits include enhanced decision-making, deeper insights into corporate operations, and facilitation of better operational processes, all of which have a substantial impact on a company's competitiveness (Maritz, Eybers, & Hattingh, 2020). The evidence shows that BDA enables firms to develop business value through intermediate organisational capacities (Benitez, Castillo, Llorens, & Braojos, 2018; Schryen, 2013). Such data-generated insights can be used to capture opportunities (Sharma, Mithas, & Kankanhalli, 2014). By utilising intangible BDAR, managers can also improve coordination, real-time resource allocation, and dynamic asset movement (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Intangible BDAR can also assist in streamlining corporate processes and identifying operational bottlenecks or service defects (Grover et al., 2018).

Intangible BDAR can enable businesses to improve their knowledge management and obtain competitive advantage (Bertello et al., 2021). In terms of intangible resources, Mikalef et al. (2018) remarked that organizational learning and data-driven culture are essential components of successful BD adoption. A data-driven culture has been identified as a critical component of a company's overall success and ability to continue working on BD initiatives (LaValle et al., 2010). Businesses with a strong data-driven culture use data extensively and create procedures to make it simple for staff members to obtain the information they need. Thus, conclusively, BDAR can give firms a competitive edge from informed and strategic decisions. However, firms must have essential competencies, skills, and strategies to utilize this.

Thus, consistent with Mikalef et al. (2019) classification, the following hypothesis is formulated:
H_2: Organizational use of intangible BDAR has a significant effect on market competitiveness.

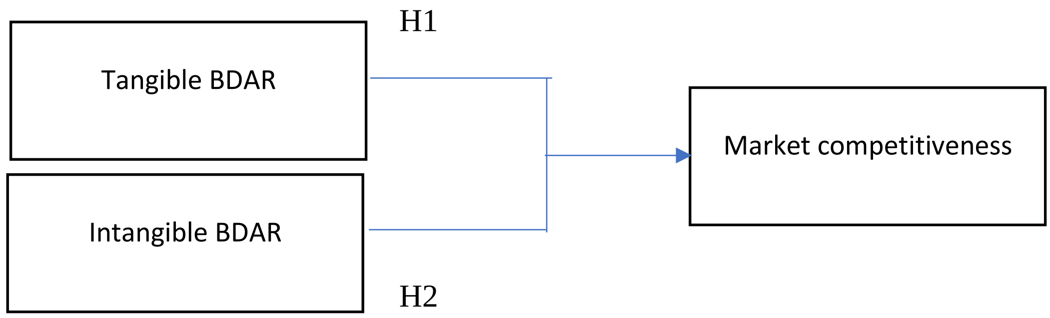

Figure 1. The schematic representation of the relationship between the study variables
Source: Authors' Conceptualisation (2023)

2.2. Theoretical Framework

2.2.1. Resource Based View (RBV)

The RBV, developed by Wernerfelt (1984) and Barney (1991), underlines the necessity for businesses to develop the skills necessary to overcome challenges and gain a competitive edge. The RBV is a management idea that concentrates on an organization's internal assets and capacities as a source of long-term competitive advantage. According to the RBV, a competitive advantage arises from particular combinations of resources that are economically valuable, scarce, and challenging to copy (Barney, 1991). Thus, a firm's mix of tangible and intangible assets, including human capital, organizational structure, knowledge, and reputation, can produce a long-lasting competitive edge. Because of their natural characteristics, such as path dependency, embeddedness, and causal ambiguity, these resources can produce a competitive advantage when heterogeneously distributed among enterprises (Barney, 1991).

The RBV is closely linked to the "VRIO;" VRIO stands for Valuable, Rare, Inimitable, and Organized. " It is a framework for evaluating an organization's internal assets and capacities to determine if they can offer a long-term competitive advantage. This study, based on RBV theory, enables firms to develop unique abilities from BDA implementation, which provides them with a competitive edge as well as the flexibility to navigate the emerging market (Aljumah et al., 2021; Alotaibi et al., 2021; Alrashidi et al., 2022). Thus, applying the RBV to the IS field implies that BDA resources that are not easily replicable, distinctive, firm-specific, and more difficult to assemble can serve as a source of long-term competitive advantage (Lu & Ramamurthy, 2011).

2.2.2. Diffusion of Innovation (DOI)

DOI was proposed by E.M. Rogers in 1962. Rogers offered the following description of an innovation: 'An innovation is an idea, practice, or project that is perceived as new by an individual or other unit of adoption' (Rogers, 2003). The result of diffusion is that people, as part of a social system, adopt new ideas, behaviors, or products. The adoption of a new idea, behavior, or product (i.e., "innovation") does not happen simultaneously in a social system; rather, it is a process whereby some people are more apt to adopt innovation than others. There were five established adopter categories.

1. Innovators: These people want to be the first to innovate. They are venturesomes that are interested in new ideas. These people are willing to take risks and are often the first to develop new ideas. Very little, if anything, must be done to appeal to this population.
2. Early Adopters - These people represent opinion leaders. They enjoy leadership roles and embrace opportunities for change. They are already aware of the need to change, and are very comfortable adopting new ideas. Strategies that appeal to this population include how-to manuals and information sheets on implementation. They do not need information to convince them to change.
3. Early Majority - These people are rarely leaders, but they adopt new ideas before the average person. That said, they typically need evidence that innovation works before they are willing to adopt it. Strategies to appeal to this population include success stories and evidence of innovation effectiveness.

4. Late Majority - These people are skeptical of change and will only adopt an innovation after it has been tried by the majority. Strategies to appeal to this population include information on how many other people have tried the innovation and adopted it successfully.
5. Laggards: These people are bound by tradition and are very conservative. They are very skeptical of change and are the hardest groups to bring on board. Strategies that appeal to this population include statistics, fear appeals, and pressure from people in other adopter groups.

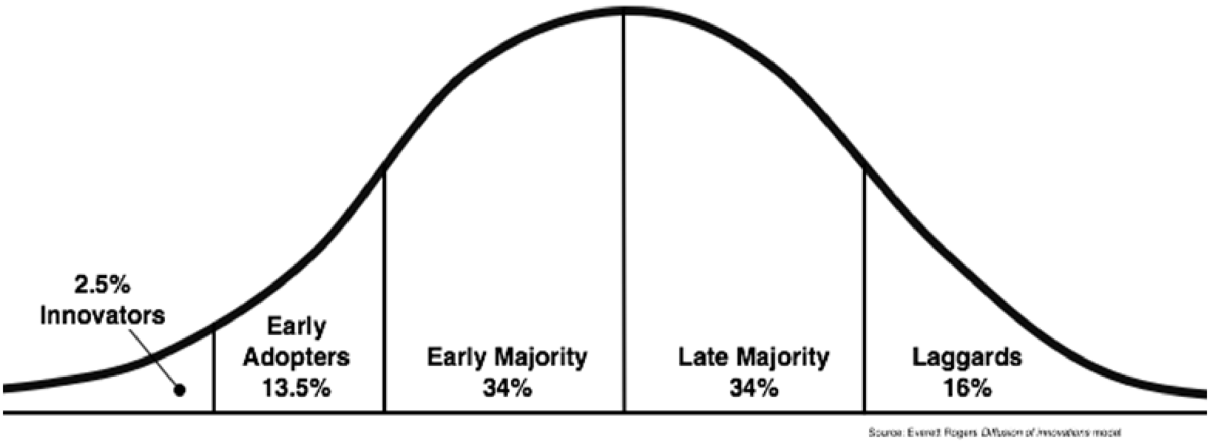

Figure 2. Phases in the diffusion of innovation
Source: http://blog.leanmonitor.com/early-adopters-allies-launching-product/

The stages by which an organization adopts an innovation and whereby diffusion is accomplished include awareness of the need for an innovation, decision to adopt (or reject) the innovation, initial use of the innovation to test it, and continued use of the innovation. Five main factors influence the adoption of an innovation, and each of these factors is at play to different extents in the five adopter categories.

a. Relative Advantage - The degree to which an innovation is seen as better than the idea, program, or product it replaces.
b. Compatibility: How consistent is the innovation with the values, experiences, and needs of potential adopters?
c. Complexity: How difficult is innovation to understand and/or use?
d. Triability: The extent to which the innovation can be tested or experimented with before a commitment to adopt is made.
e. Observability: The extent to which innovation provides tangible results.

2.3. Empirical Review

Aljumah et al. (2021) analyzed the effect of BDAC on organizational performance using a questionnaire survey of large manufacturing companies operating in the UAE. The primary data from this study, that is, from 295 questionnaires, were analyzed using the PLS-SEM approach in 2019. They found a positive relationship between BDAC and organisational performance.

Bertello et al. (2021) examined the nexus between BDA and the degree of internationalization. The authors collected information via a survey sent to the CEOs of SMEs and received 103 responses. Ordinary Least Squares (OLS) regression was used to analyze quantitative data. The study finds that while the direct effect of BDAC and the interaction term between BDA infrastructure and BDAC are both positive and significant, the relationship between the governance of BDA infrastructure and the degree of internationalization (DOI) is not.

Suoniemi et al. (2020) examined BDA's influence on firm performance. The sample was drawn from U.S., B2C, and SBU firms. The study found that BDR primarily increases firm performance by strengthening the market-directed capabilities of the firm, based on data provided by 301 senior marketing managers analyzed using PLS-SEM.

Rialti et al. (2020) analysed BDA and its influence on strategic flexibility using primary data from Europe. Survey data from 215 managers were analyzed using SEM. The findings show that BDAC significantly influences an organization's strategic flexibility. However, ambidexterity and knowledge management skills affect this relationship.

Mikalef et al. (2019) investigate the effect of BDA on firms' innovation. They collected responses from 175 chief information officers and IT managers employed by Greek businesses. These results support the fact that BDA has an indirect impact on innovative skills through PLS-SEM. They found that both incremental and radical innovation skills are entirely mediated by dynamic capabilities.

Ferraris et al. (2019) investigated whether BDAC has a favorable effect on company performance and the mediating role of knowledge management (KM) in this connection using an empirical analysis based on SEM with data gathered from 88 Italian SMEs. The results of this study demonstrate that enterprises with greater BDAC improve their performance and that KM orientation significantly increases the impact of BDA capabilities.

Popovič et al. (2018) investigated the impact of BDA on firms' high-value business performance. They studied how BDA affects operational management in the manufacturing industry. The empirical study makes use of a comparative case study of three manufacturing organizations with various levels of BDA, using an interpretive qualitative approach. The primary data that informed the hypotheses analysis to clarify the connections between BDAC and organizational performance showed that BDAC with organizational readiness factors facilitated better utilization of BDA in manufacturing decision-making and thus enhanced HVBP.

Lu and Ramamurthy (2011) studied the link between IT capability and organizational agility. They conducted a field study with matched pairs of business and IT executives in 128 businesses to experimentally investigate the relationship between a firm's IT capacity and agility. The findings demonstrate a strong correlation between IT competence and the two types of organizational agility. Additionally, they find that IT spending and capability have a considerable positive combined influence on operational adjustment agility, but not on market capitalization agility.

3. Research Methodology

3.1. Research Design

The approach used to perform the research is known as methodology (Tanha et al., 2022). This study used a descriptive survey design. According to Collis and Hussey (2005), descriptive research is "the one that describes the behaviour of the phenomena". It is used to identify information regarding the characteristics of a given problem. We used a questionnaire-based survey method for this study because it provides easy replication and generalizability of the results. To generalize the results, Straub, Boudreau, and Gefen (2004) emphasize the value of survey-based research for descriptive and exploratory studies.

Survey-based research is a well-established method for precisely capturing the overall pattern and discovering the relationships between variables in a sample. This research involved collecting and analyzing numerical data and applying statistical tests (Lim & Teoh, 2021). The primary data for this study were gathered from the respondents. The study population was comprised of respondents from manufacturing firms in Lagos State, Nigeria. The researchers purposively selected firms in the Lagos metropolis. This is consistent with the approach used by Widjaya and Padmoprayitno (2022).These companies are listed in table below as follows:

Table 1. Names of companies included in the study

S/No	Name of company	Respondents
1	African Industries Group	5
2	Nexans Kabelmetal	4
3	British American Tobacco Nigeria	14

4	Eagle Paints Nigeria Limited	4
5	Emzor Pharmaceutical Industries Ltd	12
6	Flour Mill of Nigeria Plc.	14
7	First Aluminium	7
8	Iron Products Industries Ltd. (IPI)	12
		72

Source: Field Survey (2023)

3.2. Sample Size

To determine the sample size of the study, the researcher considered the manageability of the selected respondents and therefore decided to use a non-probability sampling technique. This method requires the inclusion of all identifiable knowledge elements in the sample. Therefore, a total of seventy-two personnel with experience in marketing and ICT-related tasks were selected for this study. The decision was based on judgmental sampling considering the appropriate characteristics of the respondents.

3.3. Data Collection

According to Cooper and Schindler (2003), the researcher receives data from the study environment. In most research studies, two sources of data are employed: primary source data and secondary data sources. The study relied on primary data gathered from a structured questionnaire administered to respondents. These data were obtained first-hand by researchers from a field survey. The survey items in the questionnaire were based on previously published latent variables and their validity was supported by their psychometric qualities (Bertello et al., 2021).

3.3.1. Instrument for Data Collection

Primary data can be obtained from a wide range of sources including interviews, observations, and questionnaires. The primary data used in this study were generated from a questionnaire administered to the respondents. A questionnaire is a collection of questions or items included in a document designed to solicit feedback that is suitable for an investigation or study (Babbie, 2007). It is also believed that this method is more efficient and less time-consuming, which allows for greater control over the administration and data collection processes. The study used a structured questionnaire that required respondents to provide specific, clear-cut answers to the questions posed. The instrument was designed using a 5-point Likert scale.

3.3.2. Validity of Instrument

Validity refers to the appropriateness, accuracy, or correctness of an instrument in measuring what is intended. According to Streiner and Norman (1996), validity in relation to research is a judgement regarding the degree to which the research components reflect the theory, concept, or variable under study. The instrument was subjected to face and content validity tests. The researchers selected experts from the fields of marketing and IS who made valid inputs in the questionnaire design. According to Polit and Hungler (1999), an ideal instrument produces measurements that are efficient, unidimensional, relevant, accurate, and unbiased.

A pilot study of 10 brand marketers was conducted before fieldwork. We were able to evaluate the face and content validity of the survey items, as well as ensure that important respondents would be present and able to understand the survey as planned through the pilot test.

The respondents were assured that all of the data they provided would remain entirely anonymous and private and that any analysis would only be performed on an aggregate level for research needs.

3.3.3. Reliability of Instrument

Reliability refers to the dependability or degree to which an instrument consistently measures what it purports to do. To ensure the reliability of the survey instrument, Cronbach's alpha was used, as it is one of the most useful tests for checking the scale's reliability and consistency. Cronbach's alpha (α) was used to measure reliability with the aid of the Statistical Package for Social Science (SPSS).

3.3.4. Measurements

BDAR was measured in accordance with studies by Bertello et al. (2021) and Gupta and George (2016) as the capacity of an organization to combine, integrate, and use its BDA–based resources. Accordingly, BDAR is conceptualized and developed as a second-order formative construct. The two pillars focused on in this study were BDA-related tangible and intangible constructs. Tangible BD-related components include basic resources (e.g., financial), technology (e.g., software and hardware), and data (Wamba et al., 2017), while intangible BD-related resources are conceptualized with the underlying dimensions of data-driven culture and organizational learning. According to McAfee, Brynjolfsson, Davenport, Patil, and Barton (2012), data-driven culture refers to the extent to which organizational members base their decisions on knowledge gained through data analysis. On the other hand, organizational learning describes the focused efforts made by team members of a company to utilize their collective expertise and continuously seek new information to keep up with volatile market conditions (Teece, 2015).

The tangible Big Data Analytics resources (TBDAR) were questions A.1 – A.5 in the structured questionnaire, while the intangible Big Data Analytics resources (IBDAR) were questions A.6 – A.10 in the structured questionnaire.

Market competitiveness is conceptualized as the degree of competitiveness of the operational environment in which a firm operates (Yee et al., 2013). The MCOM comprises questions A.11 – A.17 in the structured questionnaire.

Table 2. Reliability statistics of the instrument

	N	Cronbach Alpha (□)
Intangible Big Data Analytics (IBDAR)	67	.781
Tangible Big Data Analytics (TBDAR)	67	.720
Market Competitiveness (MCOM)	67	.738

Source: SPSS ver. 23 Output

The questionnaire consists of three subscales: the IBDAR subscale consists of five items ($\alpha = .781$), the TBDAR subscale consists of five items ($\alpha = .720$), and the MCOM subscale consists of seven items ($\alpha = .738$). The instrument was found to be highly reliable, with computed α values above the .70 threshold.

3.4. Methods of Data Analysis

This refers to the methods employed to validate or refute the stated hypotheses of the study. The researcher employed a combination of descriptive and inferential statistical techniques to analyze the data. The degree of relationship was assessed using the Pearson product-moment correlation coefficient (PPMC), while the hypotheses were tested using multiple linear regression.

$$MCOM = \alpha_0 + \beta_1 TBDAR + \beta_2 IBDAR + \varepsilon_i$$

Where:

MCOM	=	Market Competitiveness
IBDAR	=	Intangible Big Data Analytics
TBDAR	=	Tangible Big Data Analytics
α_0	=	Constant
ε_i	=	Error term

3.4.1. Decision Rule

Using SPSS, 5% were considered to have a normal significance level. The accept/reject criterion is based on the computed sig. value.

Sig. Value < .05 - Reject the null hypothesis and accept the alternate; and,

Sig. Value > .05 – Accepts the null hypothesis and rejects the alternate hypothesis.

4. Results and Discussions

4.1. Demographic Information

72 copies of the questionnaires were distributed to the respondents, of which 67, which represents 93 per cent of the total questionnaire, were completed and successfully collected, and five copies (i.e., 7 per cent were not filled). A summary of the respondents' demographic information is presented in Table 3.

Table 3. Demographic information of respondents

Items	No of Responses	Percentage (%)
Sex of Respondents		
Male	39	58.2
Female	28	41.8
Years of Employment		
0 ≤ 2yrs	33	49.3
3 – 4yrs	20	29.9
5 – 6yrs	10	14.9
7yrs and above	4	5.9
Marital Status		
Single	20	29.9
Married	36	53.7
Others	11	16.4
Age Distribution of Respondents		
18 – 24yrs	5	7.5
25 – 30yrs	18	26.8
31 – 35yrs	22	32.8
36 – 40yrs	17	25.4
41yrs and above	5	7.5
Total	**67**	**100**

Source: Field Analysis, 2023

Table 3 presents the respondents' demographic information. The gender distribution section showed that 39 (58.2 %) respondents were male, while 28 (41.8%) were female. The analysis found that 33 (49.3 %) respondents had 0 to 2 years of experience, or 49.3 per cent, those had 3 to 4 years, or 29.9 per cent, those had 5 to 6 years, or 14.9 per cent, had 7 years or more were 4, or 5.9 per cent. The table also shows the respondents' marital status. Based on the analysis, 20, or 29.9 per cent; married respondents were single; 36, or 53.7 per cent; and 11 (16.4 %) were divorced, separated, or 16.4 per cent. The age distribution of respondents showed that respondents within the age bracket of 18-24 years were 5 or 7.5 per cent, those within 25-30 years were 18 or 26.8 per cent, those between 31-35 years were 22 or 32.8 per cent, those between 36-40 years were 17 or 25.4 per cent, and those that were 41 years and above were 5 or 7.5 per cent.

4.2. Descriptive Statistics

Table 4. Descriptive statistics of IBDAR, TBDAR and MCOM

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
A.1	67	1	5	4.28	1.112
A.2	67	3	5	4.42	.801
A.3	67	2	5	4.24	1.060
A.4	67	1	5	4.33	1.120
A.5	67	2	5	4.33	1.147
A.6	67	1	5	4.48	1.035

A.7	67	1	5	4.25	1.259
A.8	67	1	5	4.40	1.155
A.9	67	1	5	4.28	1.112
A.10	67	3	5	4.42	.801
A.11	67	2	5	4.24	1.060
A.12	67	1	5	4.33	1.120
A.13	67	2	5	4.33	1.147
A.14	67	1	5	4.48	1.035
A.15	67	1	5	4.25	1.259
A.16	67	1	5	4.40	1.155
A.17	67	1	5	4.40	1.155
Valid N (listwise)	67				

Source: SPSS ver. 23 Output

4.3. Correlation analysis

Table 5. Pearson correlation analysis of IBDAR, TBDAR and MCOM

Correlations

		Intangible Big Data Analytics	Tangible Big Data Analytics	Market Competitiveness
Intangible Big Data Analytics	Pearson Correlation	1	.553**	.767**
	Sig. (2-tailed)		.000	.000
	N	67	67	67
Tangible Big Data Analytics	Pearson Correlation	.553**	1	.878**
	Sig. (2-tailed)	.000		.000
	N	67	67	67
Market Competitiveness	Pearson Correlation	.767**	.878**	1
	Sig. (2-tailed)	.000	.000	
	N	67	67	67

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS ver. 23 Output

The Table above shows that IBDAR is positively correlated with TBDAR (.553**), and IBDAR is positively correlated with MCOM (.767**). The TBDAR was positively associated with MCOM (.878**). The PPMC coefficients were significant at the 1%, 5%, and 10% levels.

4.4. Test of Hypotheses

Table 6. Model summary of IBDAR, TBDAR and MCOM

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.941[a]	.885	.881	.19761

a. Predictors: (Constant), Tangible Big Data Analytics, Intangible Big Data Analytics

Source: SPSS ver. 23 Output

The M-S Table shown above is used to explain the regression model, that is, Model R (.941) R-Square (.885) and Adj. R-Square (.881) indicate that the regression model accounts for 88.1% of the variability seen in the target variable. A high R-squared value typically denotes greater variability, which the model explains. This indicates the suitability of the model for further analysis.

Table 7. ANOVA output of IBDAR, TBDAR and MCOM

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.183	2	9.592	245.620	.000[b]
	Residual	2.499	64	.039		
	Total	21.683	66			

a. Dependent Variable: Market Competitiveness

b. Predictors: (Constant), Tangible Big Data Analytics, Intangible Big Data Analytics

Source: SPSS ver. 23 Output

The statistical accuracy of the model was assessed using analysis of variance. After considering the inherent inaccuracy of the model, *the F*-value of 245.620 represents an improvement in the model's prediction. In addition, the *p*-value of .000 was much lower than 0.05. The outcome of the model is significant.

Table 8. Coefficients output of IBDAR, TBDAR and MCOM

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.651	.169		3.851	.000
	Intangible Big Data Analytics	.321	.040	.406	7.973	.000
	Tangible Big Data Analytics	.529	.041	.653	12.822	.000

a. Dependent Variable: Market Competitiveness

Source: SPSS ver. 23 Output

4.3.1. Hypothesis One

Ho_1: Organizational use of tangible BDAR has no significant effect on market competitiveness.

Since the calP-value = .000 is less than 0.05, [*t*=7.973; p-value=.000], the researchers rejected the null hypothesis and accepted the alternate hypothesis, which states that the organizational use of tangible BDAR has a significant effect on MCOM.

Evidence shows that IT enables businesses to develop business value through intermediate organizational capacities in the broader domain of IT (Benitez et al., 2018; Schryen, 2013). TBDAR assists managers in improving coordination, real-time resource allocation, and dynamic asset movements (Wamba et al., 2015).

4.3.2. Test of Hypothesis Two

Ho_2: Organizational use of intangible BDAR has no significant effect on market competitiveness.

Since the calP-value = .000 is less than 0.05, [*t*=12.822; p-value=.000], the researchers rejected the null hypothesis and accepted the alternate hypothesis, which states that the organizational use of intangible BDAR has a significant effect on MCOM. IBDAR provides businesses with access to a wealth of information on consumers and markets, helping them better understand consumer preferences, behavior, and market trends.

4.4. Discussion of Findings

For hypothesis one, the organisational use of tangible BDAR has a significant effect on market competitiveness. This is consistent with studies that used BDA and the theoretical foundation of RBV to analyse the potential of information to add value to a company (Rialti, Marzi, Silic, & Ciappei, 2018; Wamba et al., 2017). Ferraris et al. (2019), using a sample of Italian SMEs, revealed a positive correlation between BDAC and company success. Thus, BDAR helps companies make better decisions, reduce waste, and increase the quality of their products and services (McGuire et al., 2012). BDA capability in an organization is linked to broader dynamic capabilities and its potential to thrive in a competitive market (Gunasekaran et al., 2018). This is consistent with the view that with more information regarding the state of the market, the better equipped an organization is to spot new opportunities and devise fresh tactics to take advantage of them (Mikalef et al., 2019).

For hypothesis two, the organizational use of intangible BDAR has a significant effect on MCOM. Businesses can improve their knowledge management procedures and obtain a competitive advantage by utilizing their BDA capabilities (Bertello et al., 2021). It is difficult for people to react to changes outside the world. According to empirical studies, businesses that use BD-generated insights are better at identifying new risks and possibilities (Erevelles, Fukawa, & Swayne, 2016). For instance, using real-time text and sentiment analytics on social media can help businesses track customer attitudes and sentiment towards their marketing initiatives as well as how consumers respond to similar initiatives from their primary competitors (He, Zha, & Li, 2013).

5. Conclusion

Given the rapid change in the 21st century with technological evolution, manufacturing companies must utilize BDA to gain a competitive advantage. This can only be achieved using the BDA to make wise and smart decisions. The study concludes that BDA positively affects a firm's market competitiveness, as perceived by respondents. The test of hypotheses showed that the organizational use of tangible BDAR has a significant effect on market competitiveness ($p<.05$), and that the organizational use of intangible BDAR has a significant effect on market competitiveness ($p<.05$). Thus, BDA has enabled managers to have an easier time adjust their decision making more easily. Specifically, this study found a positive association between IBDAR and MCOM ($p<.05$); and a positive correlation between TBDAR and MCOM ($p<.05$). However, firms must possess the necessary competencies, skills, and strategies to utilize such capabilities. This study provides insights that are useful in helping company managers and policymakers understand how BDA can improve organizational performance.

5.1. Recommendations

Therefore, the study recommends that the following be put in place to enable the true realization of the benefits of BDA in manufacturing firms:

1. TBDA Infrastructure: Investing in TBDA infrastructure enhances an organization's overall performance. The TBDA infrastructure plays a significant role in the company, which improves the abilities required to retrieve product or service information and seize market opportunities while responding quickly to changes in the market. However, developing BDA-related skills at every level of the workforce is crucial to enhancing TBDA realization for improved organizational performance.
2. IBDA Systematization: IBDA improves knowledge management and sharing among organizational units and enhances communication among a variety of functional organizational units, assisting them in quick problem-solving and the timely creation of new products. Managers should use IBDA to learn more about their customers' businesses and provide them with insights that foster customer trust. In addition, managers must pay attention to personnel to support IBDA. The key contention is that managers must have a solid understanding of the interaction between IBDA and technology, and their potential to strategically use them.

5.2. Implications for Practice

The findings of this study have fascinating ramifications for practitioners. First, this study demonstrates that BDA involves more than just technological expenditures; it involves gathering enormous amounts of data and enabling the IT department to test cutting-edge analytics methods. This can promote an organizational learning culture by integrating BDA into business decision-making. Consequently, a company's capacity to utilize BDA to develop VRIO could potentially create value.

Second, by identifying the BDAR pillars, IBDA, and TBDA, this study can assist managers in evaluating the strengths and weaknesses of each in their organizations. The pillars that describe the aspects that collectively constitute a BDAR can reveal areas that have received insufficient funding or development. Intangible resources, such as the intensity of organizational learning and data-driven culture, can help managers appreciate the significance of these factors and develop plans to increase them across the company.

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