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Decision support model for big data analytics tools

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Background: Despite the increasing interest and investment in big data analytics (BDA), many organisations find the implementation and use of the tools challenging. This is attributed to the cumbersome nature of some of the tools.

Objectives: From both business and academic domains, this study sets out to provide a model that enables, supports, and makes the selection and use of BDA tools easier.

Method: The qualitative methods from the perspective of an interpretive approach were employed in the study. The actor-network theory (ANT) was applied as a lens to underpin the phenomenon being studied and gain a deeper understanding of why things happen in the way that they confusedly do, in the selection and subsequent use of BDA tools.

Results: The research revealed that five factors, organisational requirements, top-down versus bottom-up approach, the role of stakeholders, the usefulness of BDA, and organisational structure, primarily influence the selection and use of BDA tools in organisations.

Conclusion: Empirically, the factors bring fresh perspectives to support the decision in appropriately managing BDA deployment for organisational purposes.

Contribution: The main contribution of this study lies in the use of the decisions support model, to practically and theoretically provide a guide for managers in the organisation, in selecting BDA for decision support purposes. From an academic perspective, the study contributes to the advancement in the use of ANT for analysis in information system (IS) research.

Keywords: big data; moments of translations; organisational structure; organisational requirements; big data analytics; actor-network theory; decision support model.

Introduction

Increasingly, organisations employ big data analytics (BDA) to draw insights for commercial interests such as e-commerce and social media monitoring, as well as for public interest, which includes health data analysis and e-government service delivery (Fan & Jin 2015). Big data analytics facilitates the capturing of valuable insights from data. Organisations are generating data of unprecedented volume, complexity, and variety, and gaining meaningful insights from this data has become crucial (Zakir, Seymour & Berg 2015). Furthermore, BDA is intricately important in realising the value to enhance organisational performance.

Big data is characterised by factors that include large volume, velocity and variety (Gandomi & Haider 2015). Mohammadpoor and Torabi (2020) explicate crucial components of BDA with crucial characteristics, arguing that volume refers to the amount of data being produced and stored and veracity refers to the usefulness of the data in the analysis. Bahrami and Shokouhyar (2022) describe velocity as a big data characteristic that encompasses the speed of data collection, processing, and analysis in real time. According to Joubert, Murawski and Bick (2023), variety constitutes different forms of big data such as structured, semi-structured, and unstructured. Moreover, Cui et al. (2018) suggest that BDA can be grouped into three categories: (1) descriptive analytics; (2) predictive analytics and (3) prescriptive analytics.

For organisations to gain valuable insights from big data, the analytics process requires the use of one or more different technologies. According to Chen, Chiang and Storey (2012), the technologies for BDA include but are not limited to clustering, classification, regression, anomaly detection, neural networks, heuristic search and data mining. Jensen, Persson and Nielsen (2023) highlight some of the benefits such as faster response time to customers and improved sales. The benefits contribute to making BDA the centre of digital transformation, which many organisations are increasingly relying on for competitiveness and sustainability (Chen et al. 2014).

However, the adoption of BDA in organisations comes with its challenges. Matsebula and Mnkandla (2016) highlight some of the challenges such as deficiencies in management support; static organisational culture; a lack of architectural development and practices that do not comply with local laws on data protection. The main factors that create gaps in the application of BDA are algorithm adaption and use; facilitating contradiction; filtration of big data; and integration (Nakasholol & Iyamu 2019). None of these studies examined the influencing factors or how the challenges manifest. In many organisations, challenges exist in the use of these tools, which emanates from selecting the wrong or inappropriate tools. Some of the challenges are how to filter the most important elements of big data for service delivery (Gandomi & Haider 2015), integration of heterogeneous data (Breckels et al. 2016), and inconsistency (Joubert et al. 2023). The problem is that it is a challenge for some organisations to select and use appropriate tools that can deliver valuable insights into their business processes and information technology (IT) strategies (Chen, Lin & Wu 2020). As a result, some organisations either select multiple or none of the tools (Nyikana & Iyamu 2022).

Objective of the study

The objective of this study is to examine the factors influencing the selection and use of BDA tools in organisations. The article presents literature and the actor network theory (ANT), which underpins this study before discussing the methodology, analysing the data and concluding with the significance of using BDA tools in businesses.

Literature review

Literature is reviewed in a systematic approach. Over the years, BDA has increasingly gained attention. This is primarily because of the rise of the digital economy that has driven the growth in the demand for data storage and analytics (Zakir et al. 2015). Big data analytics utilises analytical methods to inspect, transform, and model data to extract value (Kaisler, Armour & Espinosa 2016). Along the same line of argument, Gandomi and Haider (2015) suggest that the process through which value can be gained from big data may be viewed from two main perspectives: management and analytics. According to Nakasholol and Iyamu (2019), analytical methods can enable an organisation's drivers towards operational efficiency and product innovation, to enhance business capabilities and increase competitiveness.

There are three most common big data analytical methods: descriptive, predictive and prescriptive (Wang et al. 2018). Watson (2014) states that it is important to distinguish between the three analytical methods, as the differences influence the technologies and architectures used for BDA. In addition, Sivarajah et al. (2017) assert that through the selection of analytical methods, intelligence can be mined from data sets. Big data analytics helps organisations to identify new market opportunities, take practical actions, and provide a way for enhanced strategic decision-making, which fosters competitive advantage (Zakir et al. 2015). Assunção et al. (2015) suggest that BDA brings business opportunities to organisations but taking the BDA route requires significant effort from the organisation.

Despite the potential of BDA, it poses some challenges in data processing, storage, management and acquisition (Zaman et al. 2017). Sun, Sun and Strang (2018) mentioned data transfer, security, data quality, data integration, data ownership and data protection as the challenges involved in BDA. According to Hu and Vasilakos (2016), the taxonomy of BDA can be classified into three classes: (1) big data architecture, (2) big data intelligence and (3) big data security. Nakasholol and Iyamu (2019) argue that there are incompleteness and inconsistencies in BDA tasks, which often results in discrepancies and contradictions in selecting the tools. Therefore, there is a need for decision-making capabilities in the selection of BDA tools for specific processes and business needs to avoid a continuation of these challenges.

Actor-network theory

Actor-network theory underpins the study from the angle of translation. Actor-network theory is a socio-technical theory that focuses on actors and networks and the interaction and relationship between actors and networks (Callon 1986). The ANT sees reality as organised by heterogeneous groupings of people, technology and objects (Doolin & Lowe 2002; Tatnall 2005). It is the relationships among these elements that make up reality; these relationships are posited as a network of nonhuman and human actors (Wissink 2013). Cresswell, Worth and Sheikh (2010) state that ANTS can be used by researchers that accept and aim to understand the complexities of reality such as Information System selection and adoption. It assists to theorise the different realities being experienced by a diverse set of actors to provide a more distinct depiction of the associations between actors, which is vital if one takes note of the evolving world of information systems (Mpazanje, Sewchurran & Brown 2013).

The ANT does not deny the variance between human and nonhuman actors but simultaneously emphasises that the study of associations between them must be treated symmetrically (Wissink 2013). The process of accepting and producing these associations in ANT is called 'translation', which according to Iyamu and Mgudlwa (2018), it allows for various stages of analysis. The ANT is often used to gain an understanding of how networks were created and come into existence through actors' interests and enrolments (Cresswell et al. 2010). In ANT, the moments of translation consist of problematisation, interessement, enrolment and mobilisation.

From an ANT perspective, a network is built through a four-step process known as moments of translation (Callon 1986). The first step is problematisation, whereby the primary actor seeks to identify the problem and what actors are involved in the network. The second step is interessement, the interest of other actors regarding the roles they could take on within the network evolves. Enrolment is the third step, it occurs when a network is made, and actors realise their defined roles. During the final step, the proposed solution is shared with interest groups and gains wider acceptance through the mobilisation of the actors. From ANT perspective, Walsham (1997) explains that social reality contains a mixture of objects, human and nonhuman actors, and was created for analysing circumstances where disassociating these elements is challenging.

Research methods and design

The qualitative method was employed, within which the case study following Yin (2017) and semi-structured interview technique were selected for the study. The qualitative method is selected primarily because it allows interaction with the participants, to gain a better understanding of their views and experiences in a natural setting (Leedy & Ormrod 2019). The method allowed us to facilitate the conversation with the participants (Creswell & Creswell 2018), which enabled us to gain a deeper understanding of their experiences with big data. We followed the case study approach as comprehensively defined and explained by Yin (2018), in its focus on a natural setting. The semi-structured interview was considered most appropriate for this study because it is flexible and allows participants to express their views (Babbie 2021). In the process, new questions emerged, which enriched the data.

Research participants

The choice of the financial institution was primarily because it seems to be one of the fastest-growing industries in Africa where this study was conducted. The semi-structured interview technique was used to collect data because it allows for discussion in the process, explaining complexity (Tsang 2014). One-on-one interviews were conducted with the participants. A total of 22 employees were interviewed, using technical know-how and experience as criteria to select the participants. The interview process stopped at the point of saturation, which means no new information was forthcoming. At the 18th participant, there was a repetition of information. The interviews were recorded and transcribed.

Both the organisation used in the study and participants were assigned pseudo names and codenames, respectively, to avoid disclosure of identity and maintain privacy. Thus, the organisation is named *Eclipse Finance* (EF) and the participants are referred to from 01 to 22. For ease of referencing during analysis, this format was adopted. For example, EF01, 1:1-2, which means participant 1; page number 1 of the participant's transcript; and extract from lines 1 to 2 of page 1.

Measuring instruments

Actor-network theory was selected to underpin the study, meaning it was used as a lens to guide the analysis. The thematic analysis technique was employed in the analysis of the data. The selection of ANT was primarily because of its focus on shifting negotiations. Iyamu (2021) explains that hence the theory is used to focus on examining and determining the actors and networks that exist; why the networks were created; and how the networks fuse to influence the selection and use of BDA tools in the organisation. This helps to assess the interaction of actors and their actions in influencing the selection of BDA tools in the organisation.

In achieving the objective, the analysis was conducted from three angles: (1) establish the actors and networks that exist; how the networks were formed; the roles of the various networks; and how the networks come together to influence the selection of BDA tools in an organisation; (2) through the moments of translation, examine the interaction and roles of actors, and how their actions influence the selection of BDA tools in an organisation; and (3) through the moments of translation, examine the relationship and heterogeneity of actors and networks in the formulation of criteria that guide the selection of BDA tools in an organisation.

Results

In achieving the objective of the study, which is to reveal the factors that influence the selection of BDA tools in organisations, ANT was employed in the analysis of the data collected from a financial institution. The analysis begins with identifying the actors, their roles, and responsibilities. This takes cognisance of the fact that in ANTS, the actors are both humans and non-humans (Callon 1986). This is followed by identifying and understanding the networks that exist, how the networks exist, and how they influence the selection and use of BDA occurred in the organisation. Thereafter, the four moments of translation are employed to examine how and why things happen in the way that they do in the selection and use of BDA tools (Iyamu 2021). This is carried out through an understanding of the interactions and negotiations that continually shift between actors in their various associations or groupings within the organisation.

Actor-network

Within organisations, roles and responsibilities are assigned and executed accordingly, and ultimately decisions are made. The selection, use, and implementation of BDA within the organisation exhibited a group or group of networks (Iyamu 2022). Within a network, there were networks that often replicated themselves. This is referred to as a heterogeneous network in ANTS (Heeks & Stanforth 2015). Within EF, the networks were divided into two: Information Technology (IT) and business departments (or units). From the IT department perspective, the networks involved in the selection, use, and implementation of BDA tools were the IT management project implementers, the project maintenance team and the data analytics team.

The IT management consists of various departmental managers within IT, such as the IT Infrastructure Manager, the Data and Analytics Manager, and the Technical Support Manager. Project implementers and the project maintenance team included actors that implemented and maintained the data infrastructure, which was made up of systems engineers and database engineers. The data analytics team consisted of data analysts. These networks were in collaboration as mentioned here:

> 'The ability to exploit the potential value of data is contingent upon having the right technical infrastructure and management processes, as well as the right talent.' (EF06, 4:8–9)

Similarly, within EF, the networks are divided into back-office operations (IT) and investment and business operations (Business). The IT unit included platform engineers and data engineers. The business unit consisted of market and business analysts, risk managers and compliance officers. Similarly, the networks that existed in the IT department and the actors within the business department had various roles and responsibilities that were assigned to them by the focal actors (the data and analytics manager). A network consisting of both business and IT was consciously formed because collaborative efforts and responsibilities are needed to implement BDA tools. The same IT management team was part of the executive committee of the IT department. This means that the IT management is a heterogenous network within the organisation.

The networks were identified through roles, responsibilities, and the execution of activities. The actors and networks were inextricable in the selection and use of BDA in EF. This is primarily because a group or groups (network/s) could not be constituted without actors, and no actor could work in isolation, without colleagues and facilities. In the process of selecting and using BDA tools for services, interactions and negotiations happen within the network, which ultimately requires the translation of events, activities, and services.

Moments of translation

The moments of translation of ANT are used as a lens to understand actors' roles and responsibilities, including how activities or events were negotiated and carried out in the selection and use of the BDA in the organisation. A detailed analysis follows.

Problematisation

In EF, problematisation occurs in the process of selecting and using the BDA tools. The need for BDA tools in the organisation was realised by executives who noticed the benefits of their use towards increased profitability, helping to gain competitive advantage, and minimising business risks in real time. This could be a motivating factor for the senior management in the organisation. One of the employees in EF explains as follows:

> 'We use BDA to inform investment decisions. That is a primary reason, and it is an overlying or overarching decision for the organisation. It is an overarching reason because we are an investment management firm and the decisions that we make are for investment cases and the decisions must be supported by solid evidence that the likelihood of the investment giving a return is higher and the risk of losing the value of that investment is lower.' (EF20, 1:8–12)

This implies a top-down approach, which means that the decision-makers impose a solution on the IT specialists and other employees in the IT and business units. Furthermore, areas in which BDA could prove to be beneficial are observed to be credit management, supporting investment decisions, fraud detection, and marketing. The decision-making for the selection, use, and implementation of BDA tools within EF involved the IT or Technical department heads and their teams. One of the managers explains as follows:

> 'We understood it. We knew how it operates, and how we could connect it. It has multiple connectors so to the point it can crunch any type of data, it can be an API, it can be a file or database connection, and it can be unstructured and raw data. We do not utilise it for all of those, but that's what its usability is. We first use it for integration purposes.' (EF02, 8:20–23)

The structure of EF allows the business managers within the legal, marketing and credit departments to present a business case to the Chief Information Officer (CIO). The business case is expected to focus on leveraging the BDA tools with financial data for managers and employees, to gain better insights and make effective business decisions. The goal is to ultimately grow the business, minimise customer churn and maximise profits while providing an exciting product offering to customers. It is within this goal that the CIO discussed the potential benefits of the BDA tools with the IT department heads. Based on how the discussion went, the IT department heads agreed on the benefits that can be realised using BDA tools. Moreover, according to the agreement the benefits can only be realised through the selection and use of the appropriate tool(s).

Based on the many benefits of the BDA, tools are increasingly developed. This makes it extremely difficult for many organisations, in terms of knowing what is appropriate for their organisations' objectives. Some employees in EF shared their views and experiences as follows:

> 'The reason why there is a multitude of tools out there, there's no tool that does it all.' (EF01:11–12)

> '...[*T*]hat is, out there, there are so many tools that are very good at promoting themselves. If you do not have requirements in place, you will be lost and you end up using the wrong tools.' (EF12, 3:13–16)

Thus, defining the problem of having a range of BDA tools to choose from for use and implementation could be assisted through the introduction of decision support for the selection of BDA tools. In the organisation, the procurement of BDA tools was centralised by policies, which include regulations that define commercial suppliers. This limits the involvement of organisational management and end-users (users of computer systems) in defining the requirements for selecting BDA tools. This type of limitation affects the selection of BDA tools, which ultimately shapes how the tools are used for services in environments.

Organisational structure and management (financial services, IT, and project managers) in some units propose the use of BDA tools to better understand finance-related big data that are used to carry out services daily. From the IT unit's perspective, the IT Support Head of Department (HOD) discusses the benefits of implementing and using BDA tools with his or her team members. Together, the team solicits advice from various commercial suppliers of BDA tools to decide upon the tools to select and use. In response, the commercial suppliers present various products for BDA to the team. The numerous presentations on BDA tools often confuse some members of the IT team, which makes it difficult for them to decide on a tool.

Interessement

The interest was influenced by a range of factors. Within the organisation, the actors included management, IT specialists and clients. These actors had different roles and responsibilities in the selection and use of BDA tools. Furthermore, some actors directly influenced the selection and use of BDA tools, while others had a more indirect influence. For example, clients who received services were directly influenced by BDA tools as the tools were used in analysing their feedback. In the organisation, the actors who took an interest in the selection and implementation of BDA tools included data analysts, database engineers, systems engineers, and IT management. The compliance officers and business managers took an interest in the use of BDA tools.

The IT management makes decisions on the use of BDA tools within the organisation from the executive management's viewpoint. Essentially, they assessed the need for BDA tools and the benefits of use and engaged specialists in selecting the appropriate tools. It is observed that the executive management is most likely to adopt the use of BDA in their units to bring about better management of customer requests and ensure the productivity of the organisation. Although the executive management believes in the benefits of using BDA, they see that in the implementation of new standards, the mechanism of operation may hinder the adoption as this may require additional financial investment for the training of staff. Some views are expressed as follows:

> 'Lack of skillsets; lack of tools required to carry out BDA strategies; new workflows and incentives must be designed to prioritise data-driven decision making; disruption of conventional methods may hinder the adoption of big data analytics.' (EF09, 19:90–92)

Information technology specialists included data architects, engineers and analysts. Their interest in the selection of BDA tools was triggered by the executive management needing technical expertise in the selection of appropriate tools. From the organisation's perspective, business management's interest in the use of BDA tools came from research initiatives carried out that highlight the effectiveness and benefits of the use of BDA tools in the financial services sector. Interest from the IT managers was influenced by the business management's buy-in and by the varied number of tools available for use that serve different purposes.

The interest of the IT staff stemmed from management proposals and the need for a standardised approach to selecting tools to serve different business objectives within the organisation. Furthermore, compliance officers' interest in the selection and use of BDA tools was triggered by the importance of applying correct governance structures in the implementation of technological innovations in EF.

Enrolment

Enterprises could afford to integrate phases or paralleling them to increase value and competitiveness. This could be possible if the appropriate tools are selected and deployed. This draws on the importance of the human actors that are involved or enrolled in the process.

In EF, the business managers engaged with IT managers and negotiated their participation in the selection, implementation, and use of BDA tools. Consultations and meetings were held as a basis for negotiations to occur and to entice those interested to enrol in the network of BDA tools selection and use. As both the business and IT management realised the benefits of BDA use and the significance of the selection of appropriate BDA tools in the financial sector, enrolling on this network was a success. In addition, the IT managers reached out to their subordinates to negotiate their participation in this network. The IT managers used the power conferred on them by the organisation to attract their employees to participate and assume the roles and responsibilities assigned to them during the selection and use of BDA tools.

Mobilisation

The mobilisation of activities and processes, including the communication of outcomes and dissemination of information by actors are employed differently in the financial sector. This could be associated with the nature of each unit's focus.

In EF, the business owner or manager requested analytical data to serve a specific business objective. The IT management evaluated the task components, the data structure environment, and the tools available to carry out BDA. The analysis performed by the IT management was handed over to the data analysts and architects to assess the data architecture and infrastructure and draft a plan detailing the factors in the architectural environment that will affect the type(s) of BDA tools that will be used. The data engineers and systems engineers used the plan to select BDA tools for use in the organisation.

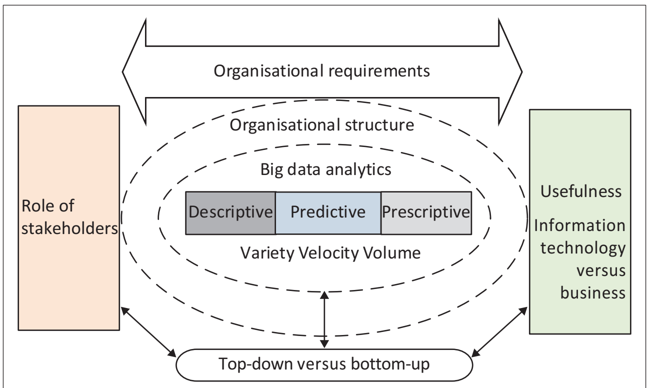
Discussion

From the aforementioned analysis, using the four moments of translation, five factors were found to influence the decision to support BDA tools in an organisation. The factors are: (a) organisational requirements, (b) top-down versus bottom-up approach, (c) the role of stakeholders, and (d) usefulness of BDA: IT versus business, and (e) organisational structure (see Figure 1). The factors are discussed next, primarily for appropriateness and within context.

Organisational requirements

Requirements define scope, object, subject, goals and objectives (Leffingwell 2010). In defining the criteria for BDA tools, two types of requirements, business and IT are involved. The requirements can either be functional or non-functional, from both business and IT perspectives (Chen et al. 2013). Functional requirements define and describe the objective and use (or usefulness) of the BDA tools in an environment (organisation). Essentially, these requirements cover aspects of an organisation's needs, such as business rules, system capabilities and processes. The requirements deal with the functionality of BDA tools. This involves evaluating organisational needs as well as BDA tools. The non-functional requirements define and describe the criteria that govern how software tools should work within an environment. Examples of non-functional requirements include reliability, usability, compliance and supportability. Furthermore, an understanding of the systems currently in place within an organisation should be considered to allow for integration possibilities.

Various varieties, velocities and volumes of data impose constantly changing requirements in deciding to support BDA tools (Demchenko et al. 2013). These are both technical (IT) (Daki et al. 2017) and non-technical (business) requirements (Gardiner et al. 2018). The business requirements include business processes, strategies, policies and human resources, which are aimed at response time, efficiency and effectiveness, whereas IT requirements include technical capabilities of BDA tools, implementation standards, and technical architecture. Requirements play a key role in the selection and usefulness of the BDA tools.



Source: Nakashololo, T. & Iyamu, T., 2019, 'Understanding big data analytics and the Interpretive approach for analysis purposes', *Journal of Contemporary Management* 16(1), 272–289. https://doi.org/10.35683/jcm18096.0014

FIGURE 1: A new model that is introduced to enable, support and make the selection and use of big data analytics tools easier.

In carrying out activities to select BDA tools, organisations rely on different networks such as end-users, software developers, business managers and IT managers for the requirements in selecting the tools. It is the approach by which data engineers and IT specialists gather non-functional and/or functional requirements from end-users and business units to aid the selection of quality BDA tools for organisations' purposes. It is therefore important to gather explicit information about the proposed analytics environment and examine the organisational needs and practices. This is a critical process in ensuring appropriateness in selecting BDA tools for efficient and functional use within an organisation (Nyikana & Iyamu 2022).

Top-down versus bottom-up approach

The decision to support BDA tools for organisational purposes should be an inclusive process and approach (Hu & Zhang 2018). However, it is not the case in many organisations. This brings about a lot of challenges that are conflicting in the selection and use of BDA tools. Based on the analysis, the selection of BDA tools in organisations is currently performed using two different approaches, i.e., top-down and bottom-up. The top-down approach refers to the management imposing BDA solutions to employees within the IT and business units. Essentially, the information system solutions to be introduced within an organisation are based on the approval and mandate given by a higher authority. Specific tasks and responsibilities are imposed upon IT and business employees. In addition, the top-down approach sees senior management according to the organisational structure initiated for the tasks needed to be carried out in the selection of BDA tools, after which team members such as data engineers and data analysts are informed of their roles and responsibilities in the BDA tools selection. The implications of this approach revolve around the fact that decision-making is guided by the roles and responsibilities being clearly defined.

The bottom-up approach implies that BDA tool selection and use are influenced and imposed by the employees within the IT and business departments to the decision-makers. It involves an organisation-wide collaboration whereby employees give their input on BDA tools and solutions. Employees provide their input on how to achieve BDA tool selection based on their expertise and day-to-day needs. This allows for more realistic task breakdowns as there is a high employee engagement and reduced risk of project failure as the capacity of employees is examined at the outset.

Role of stakeholders

The stakeholders consist of different networks such as senior management, software developers, IT managers and the business unit. Each of these groups is an expert in the roles that are assigned to them, and they take ownership. The role of each of these groups contributes to the selection, use, and management of the BDA tools within an organisation. One of the most critical networks is the business unit. The unit defines the business model, which is a fundamental role in the selection of BDA tools. This is primarily because the business model regulates the requirements for ensuring communication between various systems and the transfer of big data (Daki et al. 2017).

Various stakeholders are involved in the selection and use of BDA within organisations. The role that each stakeholder plays requires active and appropriate participation; this is because their influence on BDA tool selection and use varies considerably. For example, executive management includes people with skills and ownership responsibility to approve procurement requests for BDA tools. From a specialist perspective, the business and IT teams collaborate to elicit and formulate system design specifications that inform procurement decisions. The users use BDA tools and gain insights for analytics to meet business objectives. As such, each stakeholder's role and influence must be taken into consideration. This is the pinnacle of covert and overt power dynamics within the selection and procurement of BDA tools and depicts the cooperation between business, IT, vendors and users.

Usefulness of big data analytics: Information technology versus business

The usefulness of BDA tools crucially depends on the role of the networks (stakeholders). Müller and Schurr (2016) emphatically explain the criticality and essentiality of networks' roles in the deployment of solutions. The role of stakeholders in selecting BDA tools comprises three criteria, i.e., data management, scalable (scalability) and business strategy. Data management refers to the cycle that an organisation undergoes in acquiring and managing its BDA assets. Organisations need to consider BDA tool vendor viability when acquiring data assets. This viability should be guided by functional and non-functional requirements.

Many organisations employ BDA because of the premise that the tools are useful (Iyamu 2020). The usefulness of BDA can be explained from two perspectives, IT and business. From this perspective, some organisations employ BDA tools to foster innovation through analytics. This is achieved through the effective management of an organisation's information management and transformation cycle, which is the collection, storage, and consolidation, and the use of data to produce valuable insights. To produce valuable insights, organisations require technical infrastructure that can process and manage large volumes of data. The technical architecture covers activities such as deployment and governance, which IT is tasked with managing and includes networking infrastructure, database management systems, data integration capabilities, visualisation, reporting and infrastructure management.

Essentially, the technical environment goes through a data management cycle that begins with obtaining and procuring big data architecture and various data access protocols, structuring, and categorising data, employing algorithms and techniques to analyse the data, and finally deriving valuable insights from analytics activities. Business, in this context, is the end-user of the insights gained from the use of BDA tools. As such, the business strategy needs to be considered in the selection of BDA tools for the development of an organisation-wide data and analytics environment. This is to allow for improved operational efficiency and to enrich end-user engagement and allow for the innovation of business models.

Organisational structure

The organisational structure is the practice by which work flows through an organisation (Cosh, Fu & Hughes 2012). The organisational structure defines the levels and units, including the roles and responsibilities in an organisation. In the formulation of criteria, two important components should be associated with the organisational structure, i.e., skills and organisational culture. Skills refer to the competencies of the employees within an organisation. For the selection and use of BDA tools, an organisation needs competent staff with varied skill sets to effectively implement and use BDA tools. These include professionals such as project managers, data engineers, data analysts, and systems engineers. Otherwise, despite the appropriateness of the tools, it will be problematic. Thus, a set of criteria should guide the assembly of personnel (skills).

The explicit knowledge of an organisation lies in the structure, which makes it easier for decision-making. Moreover, activities and processes are controlled and managed through the organisation's structures. Doherty, Champion and Wang (2010) argue that organisational structures influence strategy as well as the interaction that happens between employees.

The selection of BDA tools within an organisation needs an examination of the organisational structure regarding the use of BDA. The importance is to identify and distinguish how data are being used or not used within an organisation to create a properly designed plan for the selection and use of BDA tools. Several factors can be used to assess organisational maturity in the selection of BDA tools. The skills and expertise of people within an organisation need to be examined to understand the level of skills in existence and those required to achieve effective BDA capabilities. Additionally, the technical infrastructure was installed and it required the extent to which an organisation engages in data management, the leadership and corporate culture in supporting and influencing the use of BDA tools for business processes, and the existence of effective data governance policies that govern the usage and dissemination of data that will ensure access to valuable information.

Conclusion

The selection and use of BDA tools are vital for a business's return on investment and technological fit in an organisation. Hence, appropriateness is critical. A lack of appropriateness of a BDA tool could lead to two things: (1) waste of financial investment, and (2) not being able to fulfil its purpose. These are some of the challenges many organisations have been encountering since the emergence of BDA. The challenges can be compounded because of the closeness of some of the tools. To an exponential degree, this study provides a solution for these challenges.

The factors of influence revealed and discussed can be of fundamental value to both organisation and academic domains. From the organisations' front, the factors provide more insights into business and IT managers for better decision-making. The empirical nature of the findings instils know-how in managers, in managing the process of BDA selection for a more purposeful outcome that can benefit the organisation. It is intended to save time and cost through a better understanding of the model. The contribution of the study to the academic comes from the theoretical nature of the model and its addition to the existing literature. Although this study can be most useful as claimed, there is the prospect for further studies. For example, the critical success factors for employing the model should be examined.

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Competing interests

The authors declare that they have no financial or personal relationship(s) that may have inappropriately influenced them in writing this article.

Authors' contributions

T.M.N. and T.I. are the only two authors. T.M.N. formalised the topic. T.I. guided T.M.N. in the data collection process. T.M.N. and T.I. analysed the data and contributed in writing the article.

Ethical considerations

An application for full ethical approval was made to the Faculty Research Ethics Committee and ethics consent was received on 25 February 2019. The ethics approval number is not required as all the research data is currently in the public domain.

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Data availability

The data that support the findings of this study are not openly available due to confidential interviews.

Disclaimer

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