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Research Article

Activity Theory View of Big Data Architectural Design for Enterprises

Tiko Iyamu [1*], Wandisa Nyikana [2]

[1] Professor, Department of Information Technology, Cape Peninsula University of Technology, Cape Town, South Africa
[2] Ph.D candidate, Department of Information Technology, Cape Peninsula University of Technology, Cape Town, South Africa
* **Corresponding Author:** iyamut@cput.ac.za

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ABSTRACT

The lack of architectural design leads to the fragmentation of big data and increases the complexity of an environment. This study aims to develop big data architectural design for enterprises. The qualitative method was employed, and literature relating to the study was gathered and examined. Heuristically, the data was analysed, which was guided by the activity theory (AT) as a lens. From the analysis, relationship, allocative, and interaction were found to be the fundamental factors influencing big data architectural design. Additionally, the study highlights the attributes of the factors, which include technology, governance, and transformation. Based on the factors and their attributes, a big data architectural design was developed. The proposed big data architectural design has significant implications for improving the efficiency and effectiveness of an enterprise's processes, services, and competitiveness. However, there are implications and limitations. From both information technology (IT) and business units' standpoints, the study highlights operationalisation, innovation, and integration as implications for enterprises. Non-empirical evidence is a limitation which should be considered for future studies.

Keywords: Activity Theory, Big Data, Architectural Design, Enterprise Big Data.

INTRODUCTION

The concept of big data is increasingly being explored by both academic and business domains. Big data has characteristics which include volume, velocity, variety, and veracity (Shi, 2022; Goldstein, Spatt, & Ye, 2021). This complexity requires new architectures, algorithms techniques and analytics to extract value and meaning out of big data (Jin Wang, Yang, Wang, Sherratt, & Zhang, 2020; Garoufallou & Gaitanou, 2021). Organisations use the value extracted from big data for various benefits. According to Barham (2017), big data assists organisations in developing new strategies using the insight gained. Congruently, Ravikumar, Sriram, and Murugan (2022) suggest that big data has the potential to transform organisations to operate efficiently and successfully. Another benefit highlighted by Nyikana and Iyamu (2022) is that organisations use big data to gain a better understanding of their customers. This helps the organisations know their target market, be innovative and create products and services based on the customer needs.

Primarily, many organisations do not have big data architectural design. This is a challenge, and it affects many areas such as, how the complexity of security, privacy, storage, and management are controlled and managed. Moreno, Serrano, Fernandez-Medina, and Fernandez (2018) explain that the security problems result from the fact that originally, big data was not provisioned to ensure security. Saddad, El-Bastawissy, Mokhtar, and Hazman (2020) identified challenges such as a lack of availability, scalability, and consequently query performance in handling semi-structured and unstructured data. Khine and Wang (2017) argue that traditional data warehouses are not able to store and accommodate big data. Also, conventional data architectures are not capable of meeting the demands of big data. Manogaran, Thota, and Lopez (2018), explain that the challenges above can be overcome by big data architectural design. Thus, there is a need for big data architectural design that is scalable, secure, and can handle complex datasets.

While big data provides organisations with many benefits, one cannot ignore its challenges. Mgudlwa and Iyamu (2018) highlight some challenges such as incompatibility of storage, lack of uniformity in structure, and difficulty in retrieval due to inconsistent format (Oussous, Benjelloun, Lahcen, & Belfkih, 2018). Another challenge is the velocity at which big data is generated (Chen, Kazman, & Haziyev, 2016). These challenges persist because traditional data architectures are not designed to accommodate large volumes of data (Saggi & Jain, 2018). Consequently, many organisations do not have architectural designs that can guide the rapidly increasing big data in their environments. The problem manifests in many ways, including loss of value and complexities, and they have competitiveness.

First, big data begins to lose value in the organisation, which affects its usefulness and operation. Second, the unprecedented nature of big data growth in some organisations adds to the complexities of the environment. The complexity of big data affects the software, hardware, and network infrastructure (Oussous et al., 2018; Mishra & Sharma, 2015). The problem threatens business continuity. The lack of architectural design for big data results in the data being exposed to challenges such as cyber-attacks and data breaches (Manogaran et al., 2018; Avci, Tekinerdogan, & Athanasiadis, 2020). Some of these challenges are prohibitive and hurt the efficiency and effectiveness of operations and services where big data are applied. Additionally, a lack of architectural design for big data can compromise quality including management and governance of big data in an organisation. This is a motivation for organisations to consider an architectural design for big data, to enhance business continuity, increase the efficiency and effectiveness of operations and services, and improve stability in the use of big data.

This study aims to propose a big data architectural design, purposely to enhance business continuity and improve the efficiency and effectiveness of operations and services in an organisation. Based on the aim, the study seeks to answer two questions. How can big data architectural design? What are the factors that influence big data architectural design? This study is significant to organisations including data architects because the proposed big data architectural design can be used to (1) better organise data to improve the efficiency of business processes, and (2) make IT units more effective in the service they provide to the organisation at large. In addition to answering the research question, the implications of the big data architectural design must be understood, to achieve the benefits (Y. Wang, Kung & Byrd, 2018).

Various factors, from both technical and non-technical perspectives, are involved in answering the research questions, to develop big data architectural design. From the technical front, there are various tools such as software and hardware. Roles, responsibilities, rules, and requirements are some of the factors involved from the non-technical viewpoint. These factors require actions, which necessitate interactions between actors, within context. Thus, the activity theory (AT) was considered suitable, to underpin the study. In this study, AT is used to gain an understanding of how humans interact when using or managing big data within units (communities). This includes how various rules are applied in these activities (Engeström, Lompscher, & Rückriem, 2016). We gained from Nehemia et al. (2018) explanation of how AT is used to study the activities involved in developing systems.

The article is linearly organised into eight sections. The article is introduced in the first section. The second and third sections present a review of the literature and activity theory in the context of this study, respectively. This methodology employed is discussed in the section that follows. The analysis and the conceptual architectural design are presented and discussed in the fifth and sixth sections, respectively. The next section covers the implications of the study, and a conclusion is drawn in the last section.

LITERATURE REVIEW

Big Data in Enterprises

Big data is widely described using the 5 Vs: volume, velocity, variety, veracity, and value (Al-Sai & Abdullah, 2019; Jin Wang et al., 2020; Garoufallou & Gaitanou, 2021; Belov & Nikulchev, 2021). Big data continues to evolve as organisations persistently generate large volumes of data from different sources at various levels of high velocity. Big data consists of structured, semi-structured and unstructured data sets (Nyikana & Iyamu, 2022). Saggi and Jane (2018) expand the description of big data as “a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the high-velocity capture, discovery, and analysis”. Hariri, Fredericks, and Bowers (2019) refer to it as the driving force of innovation, competition, and productivity for organisations.

Big data is redesigning the way individuals and groups think and work, and how organisations conduct their businesses. Many sectors such as health, education, entertainment, finance, and energy are using big data in various ways, to advance their operations (Mokhtari, Anvari-Moghaddam, & Zhang, 2019; Jin Wang et al., 2020; Avci et al., 2020). One of the reasons big data can be used to enhance processes, is to improve sustainability competitiveness (Dezi, Santoro, Gabteni, & Pellicelli, 2018). This helps to increase the organisation's operational efficiency and effectiveness and improve its services (Gil, Johnsson, Mora, & Szymański, 2019). According to Al-Sai and Abdullah (2019), big data provides organisations with opportunities that create business value and growth. However, for an organisation to benefit from these opportunities, it needs to have appropriate tools, applications, resources, and people engagement, which can only be enacted through architectural design. Thereafter, big data can increase an organisation's capabilities to improve its overall performance and competitiveness (Hung, Chen, Choi, & Ractham, 2021).

Despite the numerous benefits that big data brings to organisations, some of which are stated above, it has its challenges. Gil et al. (2019) highlight integration as one of the challenges of big data. Another challenge is the complexity of data sets, the traditional systems being unable to store, process, and analyse the big data (Jin Wang et al., 2020; Garoufallou & Gaitanou, 2021). Sandhu (2021) claims that some organisations have moved their big data to cloud environments, to resolve storage and processing challenges. However, that has created other challenges such as the inability to execute queries on the database that involve technology, people, and processes (Al-Sai & Abdullah, 2019). In contrast, Sivarajah, Kamal, Irani, and Weerakkody (2017) included security and privacy as challenges facing big data in some organisations. According to Sandhu (2021), it is difficult to visualise big data in real-time because of its diverse data sets. For these challenges to be addressed, an architectural design for big data is required (Ruiz, Gómez-Romero, Fernandez-Basso, & Martin-Bautista, 2021).

The Architecture of Big Data

Architecture defines a system including the relationship and interaction of its components (Tschoppe & Drews, 2022). According to Iyamu (2022a), the principles and the interactions of the components help to guide the design and governance of a system. Tupper (2011) suggests that architecture guides the construction of a system from the beginning to the end. It allows an organisation to design its current business processes and accommodate future business processes.

Big data architectural design facilitates the collecting, storing, securing, and processing of big data attributes (Yaseen & Obaid, 2020). The big data architectural design provides a plan for how data sets flow from one point to another (Kalipe & Behera, 2019). Additionally, it focuses on the business objectives and requirements to provide a holistic strategy for data sets. Also, big data architectural design helps to improve the performance of an organisation by using it to monitor and govern the operations and interconnection of processes (Costa & Santos, 2016). Avci et al. (2020) highlight that the use of big data architectural design improves data efficiency through governance.

Despite the promises of big data architectural design, it is difficult to find an organisation that has developed one (Tschoppe & Drews, 2022). Also, even though literature has highlighted many of the challenges such as integration and security (Bansal et al., 2022) and influencing factors, the development of big data architectural design is hard to find (Pääkkönen & Pakkala, 2020). This could be attributed to the method applied. Thus, we seek a different dimension by employing activity theory (AT), to underpin the study. The theory is most appropriate for two reasons: (1) it focuses on tracing and examining how an activity is performed through chains of actions by an individual or group (Nardi, 1996); and the theory is concerned with human-associated engagement, understood as activities within a specific social setting (Iyamu, 2024).

ACTIVITY THEORY

Activity theory is a socio-technical theory that has been adopted in IS studies in the last three decades (Iyamu, 2022a). The primary concern of the theory is the development of social activities (Shaanika & Iyamu, 2015). AT focuses on understanding the interactions and relationships that occur as humans perform activities (Iyamu & Shaanika, 2019a). Dennehy and Conboy (2017) explained that AT is used to understand complex human activities within a social system. Nehemia-Maletzky, Iyamu, and Shaanika, (2018) described AT as a theory of consciousness. Consciousness is a basic principle of AT in seeking to understand actions and outcomes (Kaptelinin & Nardi, 2006).

As shown in **Figure 1**, the AT model consists of six components, which are subjects, objects, tools, rules, community, and the division of labour (Park, Cho, Yoon, & Han, 2013). The components are interconnected and interrelated, indicative of the arrows in **Figure 1**. The interconnections and relationship of the components help to understand the overall activities of a system (Nehemia-Maletzky et al., 2018). Also, as expressed by AT, activities are not static, they constantly evolve due to the changes in an environment (Engeström et al., 2016).

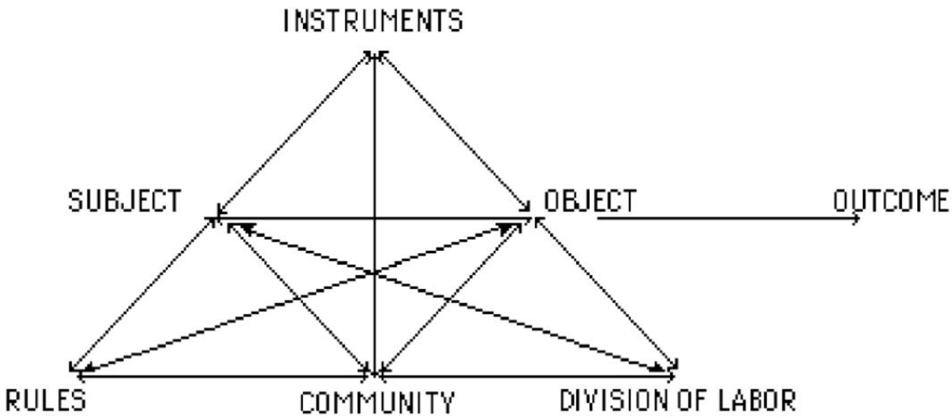

Figure 1. Activity Theory Model (Engeström et al., 2016)

In AT, a subject is an individual or group of people who perform an activity (Iyamu & Shaanika, 2019b). For a subject to act on an object, it is usually driven by motivation (Gedera & Williams, 2015). The object is the motive to initiate an activity. An object is defined by Iyamu (2022a) as the material or a problem on which the activity focuses. Tools are the artefacts used in an activity to transform an object into an outcome (Sannino & Engeström, 2018). The tools vary depending on the context of the study. Nehemia-Maletzky et al. (2018) mention some of the tools as machines, instruments, signs, procedures, and laws. A community is a collective of subjects that share the same goal, and are governed by rules (Dennehy & Conboy, 2017). The rules can be policies, procedures, and regulations. The division of labour is concerned with assigning responsibilities to members of the community (Iyamu & Shaanika, 2019a).

The suitability of AT can be described as follows: To develop the activity (big data architectural design), human (subjects) employs various tools to mediate with governance including interactions with regulations (rules). Through these actions, we gained insights into the factors that influence big data architectural design. Additionally, through AT's division of labour, we gained a deeper understanding of the roles and responsibilities of the actors using and managing big data in an environment (community) towards developing the architectural design (object). The theory has been applied in several IS studies. For example, Carvalho et al. (2015) applied AT to explain the roles of actors in the development and implementation of IT solutions. Simeonova (2018) used the theory to examine transactive memory systems and Web 2.0.

METHODOLOGY

We employed the qualitative method because it allows an in-depth understanding of the phenomenon being studied (M. Patel & Patel, 2019; Baškarada & Koronios, 2018; Tungela, Mutudi, & Iyamu, 2018; Yilmaz, 2013). This includes allowing a subjective understanding of the contents contained in the data (Tümen-Akyildiz & Ahmed, 2021). Another rationale is described by Lauri (2019), that the qualitative method seeks to understand the causes that influence the behaviours and attitudes of human beings.

Qualitative data was collected using a set of criteria that included the area of specialisation, year of publication, and sources. For specialisation, big data and architectural design were the focus. Literature of ten years, published between 2013 and 2023 was considered for selection. This was to gain an understanding of the historical background and meanings associated with the concepts (Iyamu, Nehemia-Maletzky, & Shaanika, 2016). Consequently, only a small sample of relevant literature could be gathered (Brereton, Kitchenham, Budgen, Turner, & Khalil, 2007; Glass, Ramesh, & Vessey, 2004). Literature was selected from academic databases such as AIS, IEEE, Emerald, and Google Scholar. A total of 24 relevant literature was gathered, as tabulated in **Table 1**.

Table 1. Data Source

Type	Big data	Architectural design	Total
Journal	13	5	18
Book	0	2	2
Conference	2	2	4
Total	15	9	24

Systematically, the data was processed and transformed into meaningful and valuable information (Taherdoost, 2022), to gain a deeper understanding of the factors that influence the storing, accessing, and governance of big data in organisations. This was done through analysis of the data, in which AT was used as a lens. The AT model as shown in **Figure 1** was employed by using the components to guide the analysis, as follows: (1) to examine interactions between actors and gain a better understanding of how big data are stored and governed in enterprises; (2) to fortify the fathoming of insights and evidence provided in the literature, to gain an understanding of the factors that influence big data architectural design for enterprises; and (3) to comprehend the relationships between architectural components, from both technical and non-technical factors' viewpoints.

THE ACTIVITY THEORY VIEW AND DISCUSSION

AT is employed as a lens to guide the use of the hermeneutic approach in the analysis. The focus of the analysis was threefold. Firstly, it is to gain an understanding of the activities that are involved in the use and management of big data in an organisation. Secondly, it helps to gain insights into the relationships and interactions that happen between the actors involved in the use of big data. It therefore reveals the factors that influence storing, accessing, and managing big data in an organisation. Thirdly, it focuses on the governance of big data. This uncovers how IT solutions are used or can be used at various steps, to maintain uniformity, reduce complexity, and enable flexibility in the use of big data in an organisation. A better understanding of the regulations, interactions and relationships of the actors including the regulations and governance concerning the use of big data guided the architectural design. The analysis follows AT's six components, tools, subject, rules, community, and division of labour, as presented below.

Activity Theory: Tools

An understanding of the tools guides an approach to how to apply them towards improving the manageability and governance of big data in an environment (Rao, Mitra, Bhatt, & Goswami, 2019). In the context of this study, the primary architectural tools are big data, rules, structure, and skills. Mikalef, Boura, Lekakos, and Krogstie (2019) argue that skills are critical for organisations, to gain value from big data. According to Jin, Li, Ma, and Wang (2022), deriving rules in the era of big data is of fundamental importance. Pesqueira, Sousa, and Rocha (2020) revealed that many organisations struggle with structures and skills in storing, processing, and analysing information associated with big data. The skills and structures within an organisation influence decision-making (Kamble, Belhadi, Gunasekaran, Ganapathy, & Verma, 2021). Thus, there exists a default relationship between the actors and the architectural entities such as structures and skills, which forms the basis for essential interactions.

The tools influence how IT solutions (such as big data) are implemented, managed, and governed (Mutasa & Iyamu, 2023). Interaction is defined by the relationship, and it is instrumental to how an activity is influenced. Interaction with structure produces and reproduces facility to allocate resources (Iyamu, 2010). Jinghong Wang, Zhou, Li, and Wu (2022) explained how interaction with structure facilitates learning about the attributes of information. Thus, architecture cannot be designed without a good understanding of the relationships and interactions that exist between the actors on the one hand, and on the other hand, between the actors and big data.

Activity Theory: Subject

Subjects (actors) involved in gathering, storing, using, and managing big data in an organisation are specialists with diverse skills. In AT, the subject, an actor engages in various activities within an organisation (Kelly, 2018). This can include developing and integrating IT solutions such as the design and implementation of big data architectural design. In addition, this can be an individual or a group of actors who can either be technical or non-technical (Mutasa & Iyamu, 2023). Consequently, an actor does not act alone but in collaboration with other colleagues. This makes the allocation of tasks crucial. In doing so, the relationship between the actors must first be established and defined.

The focal actor ensures appropriateness in the allocation because of its criticality. The appropriate allocation of tasks reduces the cost of operations and maximises the use of time and facilities (Yeon, Lee, Pham, & Kim, 2022). In the architectural design, different tasks and skills are required and must be aligned. Pesqueira, Sousa and Rocha (2020) explained how skills affect the transformation of big data and ultimately, shape business insights and value creation in organisations. This advances the role of individuals and groups depending on their expertise, in the implementation of big data architectural design.

Activity Theory: Rules

Big data is widely employed, yet there seem to be no universal rules dictated by architectural principles, to govern how it is stored, retrieved, and managed in many organisations. Some organisations try to adopt the same sets of principles or rules for both small and big data (Faraway & Augustin, 2018; Todman, Bush, & Hood, 2023). Consequently, this poses challenges for organisations. One of the challenges emanates because normal data technologies do not accommodate unstructured data sets such as images and videos (Saddad et al., 2020). As a result, some organisations lose out on the potential value and usefulness of their data. Hence the need for further exploring the use of big data is increasingly crucial. Nyikana and Iyamu (2023) argue that normal data and big data are not the same. The authors further argue that the differences between the two concepts include scope, volume, and heterogeneity.

Normal data is defined by Ahmed, Tezel, Aziz, and Sibley (2017) as data with structured data sets, low volumes, and constant velocities. Big data consists of huge volumes; structured, semi-structured and unstructured data sets; and high velocities (Oussous et al., 2018). The differences make it difficult to employ the same architectural design for both concepts. Jin et al. (2022) emphasised that the criticality of rules is on extracting the usefulness and providing output for new, and previously unseen value in data. He, Hung, and Liu (2023) suggest that rules enacted by individuals based on their skills are better and more manageable than machine-generated rules. This defines relationships and draws interactions between the big data and the actors (users), through comprehensible data-driven decision-making and classification tasks (Jin et al., 2022).

Activity Theory: Community

Over the years, organisations have been generating large volumes of data at an increasing rate. This has led to organisations realizing the usefulness and value of their data for business continuity (Cockcroft & Russell, 2018). This draws interest from more stakeholders in an environment, which can either complicate or improve decision-making. Kamble et al. (2021) reveal the latter, in which it is argued that the involvement of multiple groups (communities) in the decision-making process makes a difference in increasing the quality of output. Additionally, the community extend beyond an organisation through collaboration. For example, organisations from different fields such as health, education, finance, and commerce are embracing data as an asset and collaborating on projects (Hassan, Shaheen, & Sahal, 2020; Sandhu, 2021). These organisations use the data to gain insights (Garoufallou & Gaitanou, 2021) that can be used for better decision-making (Mustapha, 2022), drive business growth and stay competitive (Iyamu, 2018).

However, the speed, volume, and variety of the data they generate, make it difficult for them to collect, store, process, and analyse the data using traditional technologies (Jaiswal, Dwivedi, & Yadav, 2020). Consequently, there is a need for big data architectural design that can handle complex data sets. It is, therefore, necessary to involve many persons of diverse skills, from different stakeholder groups in the decision-making process (Kamble et al., 2021).

Activity Theory: Division of Labour

Additionally, there is a shortage of skilled data scientists, which poses a challenge since there is a demand for expertise to manage and analyse big data effectively (Mustapha, 2022). Moreover, the security and privacy of the data are another concern, as organisations need to ensure that the data is protected from unauthorised people (Sandhu, 2021). Lastly, data storage is a challenge, whereby traditional data architectures lack the flexibility and scalability to store big data (Jaiswal et al., 2020). Consequently, the activities involved in big data are broader. This necessitates the inclusion of more individuals, to ensure appropriateness in the division of the tasks.

Some of the tasks of architectural design for big data include an understanding of technical and nontechnical (business) requirements, decision-driven processes, and big data. The diversity of the tasks entails different types of skills. People with these skill sets are compulsorily required to work together, to achieve a common goal. By implication, the personnel must conjure a working relationship and interact, to fortify their tasks. Skills are critical and useful (Mikalef et al., 2019) and He et al. (2023) emphasise the importance of collective actions in enabling and supporting big data use. Other two important factors arise in the process, task allocative and appropriateness of interaction between the actors involved. These are efforts, to guide the outcome because the unintended can happen (Yeon et al., 2022).

Activity Theory: Object

Enterprises are increasingly using data to gain competitive advantage and maintain sustainability (Dezi et al., 2018). Additionally, enterprises use data to discover new insights, gain new ground, and uncover more opportunities (Dhaliwal & Shojania, 2018), to improve business decisions (Necsulescu, 2017). It is difficult to find a sector (or an enterprise) that does not employ data for its processes and activities, operationally or strategically. The education sector uses data to advance teaching and learning opportunities (Broos, Verbert, Langie, Van Soom, & De Laet, 2017). At the same time, the health sector uses the data to monitor the health conditions of patients (Izonin et al., 2021) and to make diagnoses of diseases (Mitani & Haneuse, 2020). The finance sector uses data to detect fraudulent activities (Aboud & Robinson, 2022) and to assess and manage risks (Cornwell, Bilson, Gepp, Stern, & Vanstone, 2023).

THE CONCEPTUAL ARCHITECTURAL DESIGN OF BIG DATA

From the analysis presented in the preceding section, three factors, interactions, relationship, and allocative were found fundamental to big data architectural design. As shown in **Figure 2**, the factors are interrelated and influence one another in the activities of big data, such as data gathering, retrieval, security, governance, and use. The relationship between the factors is illustrated with arrows. We summarise the interrelatedness and the influence the factors have on each other: Firstly, none of these activities could happen without interaction between the actors. This includes interaction with technology. Secondly, actors cannot interact without establishing a relationship. Thirdly, through the interaction, resources are allocated. Each factor has a container of attributes, as shown in **Figure 2**. For example, people and technology are the attributes of the relationship factors. From the AT perspective, Kaptelinin and Nardi (2018) affirmed that there is a special interest in human relationship with technology.

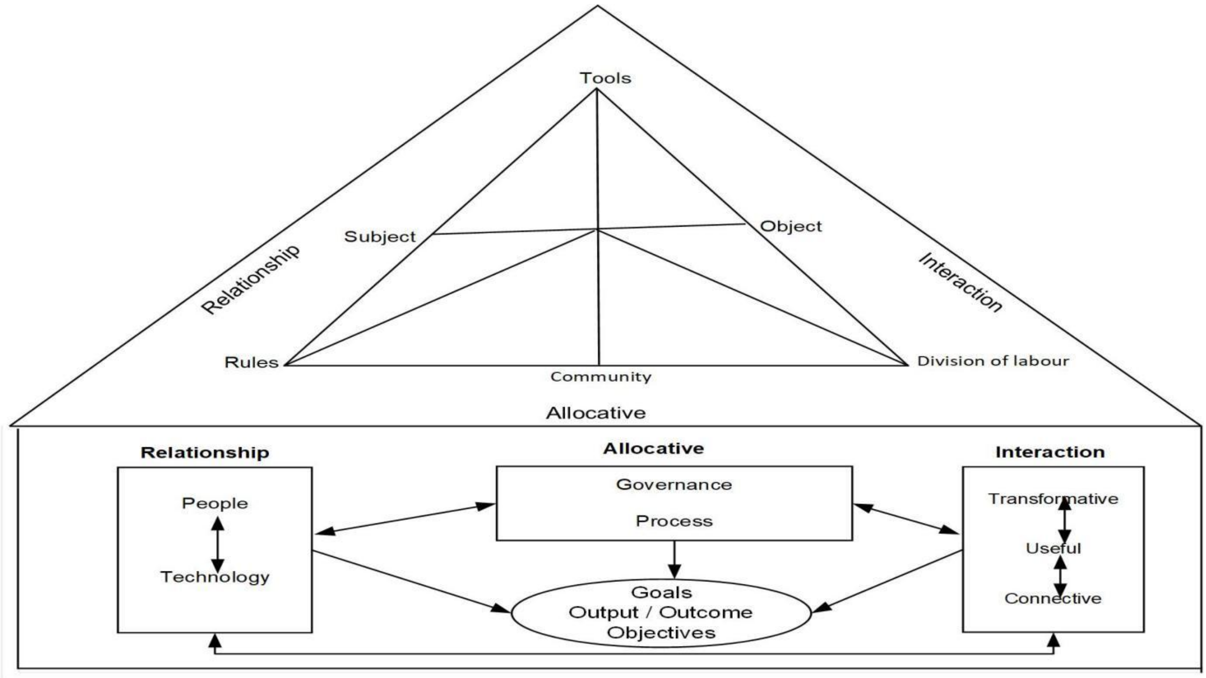

Figure 2. Conceptual Big Data Architectural Design

Relationship Between Actors and Technology Solution

Relationships anchor how humans or non-humans are connected, or the state of being connected. The relationship between actors and big data influences architectural design (Li, Ye, & Zhang, 2022). The architectural design helps to resolve issues that are durable and long-lasting in the implementation of IT solutions such as big data (Georgiadis & Poels, 2021). The architectural design expresses the relationship between humans (such as business personnel, and IT architects) and technology in employing big data to support and enable organisations.

Based on the relationship between the entities, individuals could interact and contribute to an activity using their expertise. In Giddens's (1984) explanation, systems are patterns of relations categorised into groupings within which relationships exist and interactions are carried out to produce and reproduce actions towards achieving specific goals. The architectural design draws on rules people employ to propel functioning value, which brings fort to an organisation. The relationship between the two entities, people, and technology, is enclosed in rules and compliance, which regulate their interaction and functioning (Iyamu, 2022a). Employees fall back on such architectural value in times of interpretation and challenges. The relationship between the entities defines and shapes their interaction. In return, the interaction shapes the relationship. Giddens (1984) refers to this as reproductive, stating that through activity, agents reproduce the conditions that make these activities possible.

Interaction Towards an Outcome

Interaction between actors and interaction with the rules and big data, together, ensure an outcome (architectural design). The interaction manifests into transformative, useful, and connective in the big data architectural design. Iyamu (2022b) suggests that architecture is a synthetic approach to interacting with big data for organisational purposes. Interaction with rules and IT solutions (such as big data) is often geared toward the transformation of activities and business objectives, which is, however, not always straightforward. Habitually in many environments, it requires interpretations, which are often subjective, with different meanings. As a result, collaboration among the actors remains a formidable option or solution to bridge the gap created by subjective understandings. It helps to integrate the contributions of individuals with diverse views and perspectives in addressing transformative initiatives.

In the process of architectural design, the actors must be reciprocally active in their interactions, to share requirements, ideas, and knowledge towards usefulness. Van Wessel, Kroon, and De Vries (2021) emphasised the need for the interaction between business and IT units, to fortify an organisation's better usefulness of IT solutions. Consequently, the rules used are reproduced, various skills are employed to deeply engage with content, and tasks are appropriately distributed. Li, Ye, and Zhang (2022) argue that there must be new ways of interacting with big data, to promote its usefulness. In the context of this study, interaction from connective can be divided into functional and non-functional.

Functional interaction occurs between humans (actors), it entails the interpretation of context and the exchange of ideas among the stakeholders. The non-functional interaction occurs between humans and non-humans, such as rules and IT solutions. Manogaran et al. (2022) argue that the challenges lie in human-computer interaction with big data. The significant role and the diverse nature of interaction make it cumbersome. The interaction between the actors enables the allocative of resources. Giddens argues that resources cannot be developed without interaction that gives power to allocate. According to Giddens (1984), allocative resources may be understood as involving the control of information or knowledge.

Allocative as an Enabler

Governance and process are the attributes of allocative, through which resources are employed to develop big data architectural design. Allocative is shaped by governance and processes, and it constitutes rules that define boundaries within which activities are carried out. Also, the rules do not enforce themselves. Compliance with the use and management of big data is a challenge in many organisations (Georgiadis & Poels, 2021). Allocative efficiency necessitates the distribution of tasks among the actors, in the implementation of big data architectural design. Primarily, this navigates and fosters the interaction of aligned interests of both business and IT architects (Iyamu, 2022b).

Primarily, one of the challenges in many environments is the inappropriate distribution of tasks in the design, implementation and management of IT solutions including big data. As a result, challenges linger in the efficient use of big data for organisational purposes. Thus, governance becomes fundamentally important. Governance defines the standards, principles, and policies within which events and activities are performed. According to Iyamu (2022b), allocative is influenced by policy, and implementation of standards and principles, in the development and implementation of architectural design in organisations. Allocative efficiency allows the gathering of holistic technical and business requirements, accessing more accurate information, and more inclusive decision-making, to guide big data architectural design.

CONCLUSION

This study advances our understanding of the complex interplay of factors influencing the architectural design of big data. By applying Activity Theory, we identified three key factors that shape this process: relationship, interaction, and allocative. These findings highlight the multifaceted factors including attributes involved in big data architectural design, emphasising the need for holistic approaches that consider technological, organisational, and human dimensions.

Theoretically, the study contributes to the literature on big data in organisations by providing a nuanced perspective on how architectural design can be integrated with both IT and business solutions. The study also demonstrates the utility of Activity Theory in understanding complex organisational phenomena. Practically, our findings suggest that organisations need to focus on developing comprehensive strategies that address the attributes of the factors identified. This includes investing in employee training for operationalisation purposes, fostering a culture of innovation, and fostering a culture of innovation strengthening integration structures between IT solutions and business processes.

However, the study also has some limitations, such as the focus on a non-empirical or case study approach. Future research should aim to validate the findings in organisational settings and explore the feasibility and impact of big data architectural design from both technology and business perspectives.

IMPLICATIONS

The study has some implications for an organisation that deploys big data, as tabulated in **Table 2**. Ghasemaghaei and Calic (2019) emphasised that the relationship with big data contains significant theoretical and practical implications. The implications of this study, Operationalisation, Innovation, and Integration, are viewed from both technical (IT unit) and non-technical (business unit) standpoints.

Table 2. Implication of the Study

Components	IT unit	Business unit
Operationalisation	TOperationalisation (implementation and use) of the architectural design requires defining the enabling and supporting technologies by employing governance principles. Batyashe and Iyamu (2020) suggest that an operationalisation approach must be developed, to enable and support an IT solution.	Business units' understanding of big data architectural design operationalisation may require training. This helps to gain insights into the influencing factors, to leverage the utilisation of big data to improve efficiency and performance (Calic & Ghasemaghaei, 2021).
Innovation	The architectural design requires practice that must be measured, to assess its value to the organisation. According to Babu, Rahman, Alam, and Dey (2021), innovation concerning big data has implications that could influence efficiency and effectiveness.	Business units may need to gain comprehension of how big data architectural design can be used as an innovation, to improve processes, effectively. Iyamu (2022a) suggests that such understanding can be used to reduce costs, minimise the total cost of ownership (TCO), and increase competitiveness.
Integration	For cohesion, the integration of big data architectural design and other IT solutions is required. Y. Wang et al. (2018) suggest that it is critical to employ architectural design in addressing big data component functionalities. It creates opportunities and challenges for the alignment of skills (Iyamu, 2022a).	The integration of big data architectural design with business processes is essential, to improve efficiency and effectiveness in the organisation. Ethiraj and Posen (2014) explained from a business viewpoint, an implication of architectural design lies in interconnectivity with products.

An understanding of the implications of deploying big data is significant, to improve organisational efficiency and performance. From the operationalisation and strategic perspectives, there are factors, which influence the practice of big data architectural design. Thus, organisations must develop an operational approach to support the architectural design. From the innovation perspective, the IT unit needs to develop an approach that can be used to measure the value of architectural design to the organisation (Acciarini, Cappa, Boccardelli, & Oriani, 2023). The business units need to understand how big data architectural design can be used as an innovation, to improve competitiveness (Sestino & De Mauro, 2022). Integration remains an iterative approach, for the unification and coexistence of IT solutions and business artefacts, to reduce complexity, increase effectiveness and efficiency, promote seamlessness of processes, and enable product interconnectivity (Qi, Xu, & Rani, 2023; Dwivedi, Moktadir, Jabbour, & de Carvalho, 2022).

ETHICS STATEMENT

The study does not require ethics committee approval. This is because the study does not involve human engagement. Also, animals were not used in the study. As discussed in the manuscript, literature was used as data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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