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# The implications of the dimensions of data change for organisations' usefulness

**Wandisa Nyikana,** *Cape Peninsula University of Technology, Nyikanaw@cput.ac.za*
**Nomawethu Tungela,** *Cape Peninsula University of Technology, TungelaN@cput.ac.za*
**Tiko Iyamu,** *Cape Peninsula University of Technology, IyamuT@cput.ac.za*

## Abstract

The evolution from traditional (small) data to big data has had various dimensional implications in its accumulation and use by organisations. How and why the factors that manifest into the implications occur remain challenging in many quarters. This study sets out to examine and guide an understanding of the implications of the dimensions of data change for organisations' purposes. This study employed the systematic review technique to gather literature about data, from its evolution and theory to practice. The hermeneutics approach is applied in the analysis within the frame of structuration theory's dimension of social change. The analysis reveals the implications of the dimensions of data change from organisations' standpoints. The findings of the study are significant from important points. Firstly, it accounts for the implications which create opportunities to increase the usefulness of data for organisations. Secondly, the study advances the use of dimension of social change from the use of data perspective.

**Keywords**: data evolution, structuration theory, dimension of social change, small data, big data

## Introduction

Data has been used in many areas including production, healthcare, and research for many decades. Lee (2017) explains that the evolution of data began in the early 1950s, as he discusses the act of defining, gathering, storing, and managing large volumes of data. Based on data, Kendrick (1961) discusses the prediction of service, which had its route on historical components. The evolution continued into the 1970s and 1980s when abstraction and classifications of data were dominant (Navathe, 1992). Between the 1960s and 1980s, the speed and variety of data increased, which required different approaches for storing and management of data. This change has various implications for both technologists and commercial entities.

As we moved into the 20th century, the evolution of data sped up and challenges grew in different directions. One of the challenges, from both business and academic research perspectives, was limited data collection and storage ability (Davenport & Dyché, 2013). The evolution of data makes the pre-factual or rhetorical increase in the implications of its complexity (Kuo & Kusiak, 2019; Kitchin, 2014). encounters challenges such as a lack of data-driven culture and technological culture (Dwivedi et al., 2023). These challenges have implications for innovation, in determining the spread of data, sources of data, and data futurism (direction), for competitiveness and sustainability purposes.

Some of the challenges are related to fragmentation, redundancy, and distributed transaction processing of data (Navathe, 1992). The diverse nature of data makes it cumbersome as it grows in volume, veracity, variety and evolute. According to Kitchin (2014), data are diverse in their characteristics, which shape

explicit terms of use and management. The implication increases as organisations strive to build capabilities to leverage data, for competitiveness (Lee, 2017). Dwivedi et al. (2023) provide a detailed explanation of inequality of access as an implication that leads to asymmetry in the data used and management in many organisations.

From small data of the 1950s (Zhu et al., 2014; Lee, 2017) to big data and the point where the distinction between them becomes a concern and challenge (Acciarini et al., 2023; Nyikana & Iyamu, 2023b), demonstrates the significance of the implications of the evolution. Even though many organisations including government administrations and agencies have suffered the consequences of the evolution of data, the implications remain a mystery or hard to pin down. This is attributable to the intangible nature of the consequences and varied challenges. Also, the implications are often not known or realised immediately. These ontological assumptions trigger the objectives of this paper, which are to determine the implications of the dimensions of data evolution for organisations and develop a conceptual framework that helps to determine the factors. This is highly significant primarily because we have not seen the end of data evolution.

Thus, three things are fundamentally critical. First, to understand the trajectory of data in organisations' contexts. Second, to examine how to align the speed of data evolution with the organisations' activities, goals, and objectives. Third, to gain a better understanding of how data are classified as they evolve and manifest in the process and activities they are used to enable and support, for organisational purposes. Based on the objective, Giddens' (1984) dimension of social change of structuration theory is employed to underpin the study. Dimension of social change encompasses four cardinal points, namely the Origin, Type, Momentum, and Trajectory, which are concerned with sources, change, pace, and direction respectively, within a social structure (Giddens, 1984).

This paper is organised into seven sections. The first section represents the introduction, followed by a literature review in section two. The theory underpinning the study is presented in the third section. The fourth, fifth and sixth sections discuss research methodology, analysis and discussion, and the conceptual framework, respectively. The conclusion is drawn in the last section.

## Literature review

Data is considered a valuable resource that assists organisations to generate insights and drive innovation (Nyikana & Iyamu, 2023c). It is used by some organisations, to gain business opportunities, maintain sustainability (Dhaliwal & Shojania, 2018), and provide a competitive advantage (Dezi et al., 2018). These make organisations rely more on data to gain insights and improve service delivery. For example, in healthcare, data is useful to diagnose illnesses and monitor patients' health (Hassan et al., 2019). While in finance it helps to detect fraud and assist with risk management (Aboud & Robinson, 2022). However, some organisations struggle to make sense of a large, variety of data (Iyamu, 2023; Cockcroft & Russell, 2018). This is due to many factors such as the analysing, processing, management or interoperability (Sandhu, 2021; Wang et al., 2020), which are often influenced by change, direction, and type of data.

In modern business, data are immensely valuable and useful to the extent that many organisations wholly depend on it for service delivery, sustainability, and competitiveness. The criticality of data contributes to its speedy evolution, from small to big data. From Iyamu's (2019), argument, data are raw materials that are meaningless and cannot be considered right or wrong. Hence, the usefulness of data is achieved after it has been processed into information, which is not always easy or simple in many organisations. The meaninglessness, right or wrong is increasingly a major challenge in many environments because some

organisations find it difficult to contextualise. Often, this is caused by a lack of understanding of the data growth speed and trajectory in the context of an organisation's objectives and requirements.

Data evolution continues. Jones (2019) draws a picture of how data shifted from what it used to be, to how it is now. This includes a change from relying on sample data to entire data as well from casual to correlation explanations. Additionally, another change is in the data sets, from structured and semi-structured to unstructured datasets (Ravikumar et al., 2022). With the evolution of the data, the traditional methods used to collect, store, and analyse data, are no longer capable of dealing with big data (Shaanika & Iyamu, 2020). This is due to the complexity of big data, rising from the huge datasets, high speed, and the variety of data types (Goldstein et al., 2021). This results in some organisations investing in cloud-based solutions hoping to resolve the challenges (Sandhu, 2021).

The rapidity of the data evolution can be attributed to its categorisations, in attempts to streamline its value and usefulness for an organisation's purposes. The categorisation leads to differentiation into small data and big data (Qian et al., 2022). This has not solved some of the challenges encountered in many organisations. Kitchin and McArdle (2016) argued that small data has some characteristics of big data, hence its complexity is smaller. The challenges include the selection of tools for the analytics of the data, for which, Nyikana and Iyamu (2023a) propose a formula. This formula has neither been tested nor evaluated, therefore, the problem remains.

Data evolution manifests and poses challenges in many organisations. Thinyane (2017) argues that the description or categorisation of data, whether small or big, focuses on the size and how it is collected and processed. This requires an understanding of the influencing factors as they manifest from the origin, types, trajectory, and momentum dimensions to effect data change within a context. A lack of understanding of these factors can be attributed to why some organisations still have fragmented data stored in legacy systems (Bahri et al., 2018). Gil et al. (2019) suggest that the integration of the data from the silos becomes a challenge and it affects the comprehensive view of the organisational data and the ability to gain insights. As data evolves, so do the challenges with the quality and integrity of the data (Rattan, 2018). This aspect is essential as it ensures that data is accurate and complies with the regulations. For instance, the relational databases that were used to store and process small data are no longer capable of dealing with the increasing data (ElDahshan et al., 2022).

As data and its evolution continue to pose challenges for many organisations, in response, various solutions and approaches are consistently sought. On the one hand, small data is being separated from big data to sanitise and promote its usefulness (Nyikana & Iyamu, 2023b; 2023a), and data analytics tools are employed to increase the value and sustainability of data in organisations (Sandhu, 2021; Wang et al., 2020). From other perspectives, cloud solutions are deployed to reduce complexity and improve data management and reliability (Murthy et al., 2020). Despite these efforts, the challenges remain. Hence, it is fundamentally important to explore and examine other root causes and influencing factors. Thus, the dimension of social change of structuration theory (Giddens, 1984) is employed to underpin the study.

## Dimension of social change

Dimension of social change is a component of structuration theory (Giddens, 1984) that is employed as a lens in information systems (IS) research. Structuration theory is concerned with the relationships that exist between structure and agency, which extend into the focus of the dimension of social change (Hughes et al., 2022). The dimension of social change is described by Del-Shamarran (2022) as episodic, meaning a social life has a beginning and an end. The dimension of social change consists of four components origin, type, momentum, and trajectory in its cardinal points alike, as shown in Figure 1 (Giddens, 1984). An

episode travels from the beginning towards the end at a certain speed which possibly occurs using different routes. Tungela et al. (2018) explain that the nature of different types of episodes can be assessed using the dimension of social change, to gain a deeper fathom of the associated circumstances.

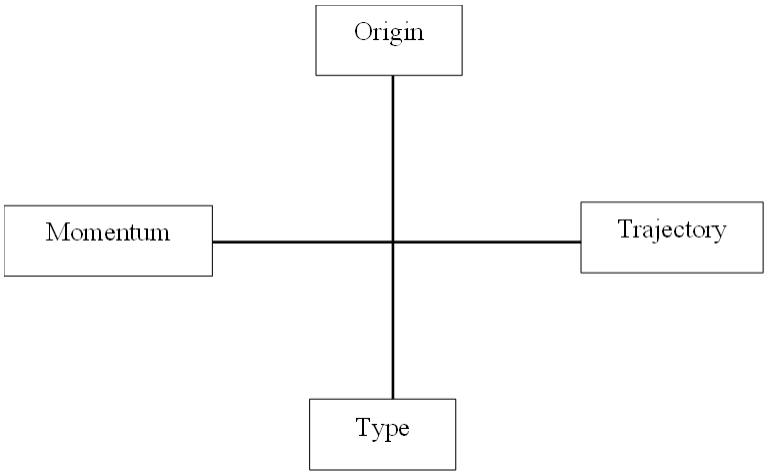


**Figure 1: Dimension of Social Change (Giddens, 1984)**

Origin is concerned with establishing the source and history of an episode (Giddens, 1984). This element assists to trace and examine the source and history of big data. Type highlights both the negative and positive impact that change has on an entity (Tungela et al., 2018) including the distinctive modes or nodes of information about an episode (Iyamu, 2021). Momentum refers to the pace or rate at which change occurs in a particular episode (Tungela et al., 2018). This guides comprehension of how data has transformed into big data over time setting direction and use. Yokoyama (2010) asserts that trajectory is the specific direction of social change. According to Boje et al. (2017), change is not a straightforward process but rather complex because of a variety of influencing factors.

In attempts to understand the implication of the dimensions of data change, tacit knowledge gained from practical consciousness is fundamental. Giddens (1984 p. 23) describes practical consciousness consists of all the things which actors know tacitly about how to 'go on' in the contexts of social life without being able to give them direct discursive expression. The dimensions of change help to rationalize our understanding of interactions and actions within a diverse environment, such as the accumulation and use of big data, in its 3-dimensional nature: (i) veracity, velocity, and volume (Mikalef & Krogstie, 2020); (ii) structured, semi-structured, and unstructured datasets (Nyikana & Iyamu, 2022; Goldstein et al., 2021); and (iii) its transformation of processes and activities (Grover et al., 2018; McAfee & Brynjolfsson, 2012).

## Research methodology

Based on the objectives of this study which is to determine the implications of dimensions of data evolution for organisations, the interpretive approach from the qualitative paradigm is employed. The rationale for following the qualitative method is it is rooted in exploring and understanding complex phenomena in their natural setting (Sovacool et al., 2018; Tsang, 2014). Making it suitable to explore and understand the implications of dimensions of data evolution for organisations. Another reason for selecting the qualitative method is that it does not focus on statistical analysis like quantitative (Gravetter & Forzano, 2018), but rather on subjective experiences, opinions, and views (Tümen-Akyildiz & Ahmed, 2021). Hence, it is adopted to gain rich information about the factors that influence the dimensions of data change.

The qualitative data was collected using a systematic review technique. The systematic review allows the search, assessment, and analysis of existing literature relating to the phenomenon being studied (Dawarka & Bekaroo, 2022). Also, it helps to provide a historical background of a phenomenon over some time (Iyamu et al., 2016). Making it suitable to cover the evolution of data over time, from small to big. The criteria that guided the collection of data were based on time and source.

Data was collected focusing on the material published between the year 2013 and 2023. The 10-year period assists in providing stable and broad coverage of existing material. This helps to evaluate the transformation of data from small to big data. There were other materials reviewed that were older than 2013. These materials covered the first evolution of data, from as far as the year 1950. Themes were extracted from the research title and were used as keywords, to search the databases. Some of the themes are small data, traditional data, big data, and the evolution of data. Academic databases such as Google Scholar, IEEE, EBSCOhost, and Emerald were consulted to collect the data. The material included different types such as journals, books, book chapters and other papers related to the phenomenon under investigation.

A total number of 63 documents (materials) were collected. After a thorough scrutinising guided by the objective, 39 of the materials were found to be most related and appropriate for the study. Table 1. presents a sample of the materials that were collected. The materials are from a spectrum of sources, which include books, book chapters, Journal outlets, and Conference Proceedings.

**Table 1: Small Data and Big Data Selected Material**

| Title | Conference Proceeding | Journal | Book | Book chapter |
|---|---|---|---|---|
| **Small Data** | | | | |
| Aboud & Robinson. (2022). Fraudulent financial reporting and data analytics: an explanatory study from Ireland. | | X | | |
| Dezi, Santoro, Gabteni & Pellicelli. (2018). The role of big data in shaping ambidextrous business process management: Case studies from the service industry. | | X | | |
| Dhaliwal & Shojania. (2018). The data of diagnostic error: big, large and small. | | X | | |
| Faraway & Augustin. (2018). When small data beats big data. | | X | | |
| Hassan, El Desouky, Elghamrawy & Sarhan. (2019). Big data challenges and opportunities in healthcare informatics and smart hospitals. | | | | X |
| Kitchin, & McArdle. (2016). What makes Big Data, Big Data? Exploring the ontological characteristics of 26 datasets. | | X | | |
| Qian, Huang, Yang & Chen. (2022). Data science for oceanography: from small data to big data. | | X | | |
| **Small Data Total** | | **6** | | **1** |
| **Big Data** | | | | |
| Ali, El-Sappagh, Islam, Ali, Attique, Imran & Kwak. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. | | X | | |
| Bahri, Zoghlami, Abed & Tavares. (2018). Big data for healthcare: a survey. | | X | | |
| Chodak, Suchacka, & Chawla. (2020). HTTP-level | | X | | |

| Title | Conference Proceeding | Journal | Book | Book chapter |
|---|---|---|---|---|
| e-commerce data based on server access logs for an online store. | | | | |
| Cockcroft & Russell. (2018). Big data opportunities for accounting and finance practice and research. | | X | | |
| Dash, Shakyawar, Sharma & Kaushik. (2019). Big data in healthcare: management, analysis and future prospects. | | X | | |
| ElDahshan, Selim, Ebada, Abouhawwash, Nam & Behery. (2022). Handling Big Data in Relational Database Management Systems. | | X | | |
| Gao, Wang, Helu & Teti. (2020). Big data analytics for smart factories of the future. | | X | | |
| Garoufallou & Gaitanou. (2021). Big data: opportunities and challenges in libraries, a systematic literature review. | | X | | |
| Gil, Johnsson, Mora & Szymański. (2019). Review of the complexity of managing big data of the internet of things. | | X | | |
| Goldstein, Spatt & Ye. (2021). Big data in finance. | | X | | |
| Hussein. (2020). How many old and new big data v's characteristics, processing technology, and Applications. | | X | | |
| Hussien, Yasin, Udzir, Ninggal, & Salman. (2021). Blockchain technology in the healthcare industry: Trends and opportunities. | | X | | |
| Li, Liu, Sun & Zhu. (2022). Challenges of industrial engineering in big data environment and its new directions on extension intelligence. | | X | | |
| Löfgren & Webster. (2020). The value of Big Data in government: The case of 'smart cities'. | | X | | |
| Jones. (2019). What we talk about when we talk about (big) data. | | X | | |
| Meadows, Merendino, Dibb, Garcia-Perez, Hinton, Papagiannidis, Pappas & Wang. (2022). Tension in the data environment: How organisations can meet the challenge. | | X | | |
| Meneghello, Thompson, Lee, Wong & Abu-Salih, (2020). Unlocking social media and user generated content as a data source for knowledge management. | | X | | |
| Murthy, Shri, Kadry & Lim. (2020). Blockchain based cloud computing: Architecture and research challenges. | | X | | |
| Nyikana, W. & Iyamu, T. (2023b). The taxonomical distinction between the concepts of small data and big data. | X | | | |
| Nyikana & Iyamu. (2023a). A Formulaic Approach for Selecting Big Data Analytics Tools for Organizational Purposes. | | | | X |
| Nyikana & Iyamu. (2022). A Guide for selecting big data analytics tools in an organisation. | X | | | |
| Otto. (2022). The evolution of data spaces. In Designing data spaces: The ecosystem approach to competitive advantage. | | | X | |
| Pääkkönen & Pakkala. (2020). Extending reference architecture of big data systems towards machine learning in edge computing environments. | | X | | |
| Pervaiz, Vashistha & Anderson. (2019). Examining the challenges in development data pipeline. | X | | | |
| Ranjan & Foropon. (2021). Big data analytics in building the competitive intelligence of organizations. | | X | | |
| Rattan. (2018). Data integrity: history, issues, and remediation of issues. | | X | | |

| Title | Conference Proceeding | Journal | Book | Book chapter |
|---|---|---|---|---|
| Ravikumar, Sriram & Murugan. (2022). Applications and Risks of Big Data in Financial Services. | X | | | |
| Salunkhe. (2023). Secure sharing of healthcare data using a decentralized blockchain network for the Internet of Medical Things. | | X | | |
| Sandhu. (2021). Big data with cloud computing: Discussions and challenges. | | X | | |
| Sestino, Prete, Piper & Guido. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. | | X | | |
| Wang, Yang, Wang, Sherratt & Zhang. (2020). Big data service architecture: a survey. | | X | | |
| Zhang, Chen, Du, Yuan, Kadoch, & Cheriet. (2020). Real-time remote health monitoring system driven by 5G MEC-IoT. | | X | | |
| **Big Data Total** | **4** | **26** | **1** | **1** |
| **Total = 39** | **4** | **32** | **1** | **2** |

## Analysis and discussion

Analysis was conducted on the data, to provide meaningful information (Taherdoost, 2022; Cassell & Bishop, 2019). The hermeneutics approach was employed for the analysis of the data, from the interpretivism viewpoint. This is because the hermeneutics approach focuses on how different individuals make sense of their experiences to interpret the world around them (Thirsk & Clark, 2017). The approach entails going back and forth within the data (Nyikana & Iyamu, 2022), to understand the factors that influence the transformation of processes and activities. This is done by subjectively interrogating the text in the data set, to extract fresh perspective, to form new knowledge (Nigar, 2020), from the dimensions of data change caused by the veracity, velocity, and volume as well as the structure of datasets. The hermeneutics approach was guided using the dimension of social change from structuration theory, as presented in Table 2.

**Table 2: Evolution of Data through Dimension of Social Change**

| Origin | Trajectory |
|---|---|
| Data comes in different forms and sources making them beneficial and challenging at the same time (Ali et al., 2021). The origin of data is neither static nor from a single channel. Primarily, there are three individual, enterprise, and technological levels of data origins. The first level focuses on individuals because data originates from people (Dash et al, 2019). For example, when an individual visits a healthcare facility, their data is captured to open a medical health record (Tungela et al., 2018).<br>At the second level, the enterprise is the custodian of the data collected about individuals and their activities. At this level, data is generated from sources such as social media interactions and online activities (Meneghello et al., 2020). The data generated from these sources consists of structured, semi-structured, and unstructured datasets (Hussein, 2020). This means that the data is raw and unrefined. Unrefined data has | Data has evolved from small (traditional) data to big data. Big data was initially characterised by the 3 V's which are volume, velocity, and variety (Garoufallou & Gaitanou, 2021). While some organisations struggled to grasp the fundamentals of big data and its characteristics of 3Vs, it has evolved into 5 v's by including veracity and value (Sandhu, 2021). The evolvement is a result of the transformative process and need for data by individuals and organisations.<br>As the data grows, so do the challenges posed by the complexities of big data to individuals (Li et al., 2022), organisations (Ranjan & Foropon, 2021) including government administrations (Löfgren & Webster, 2020). These challenges are due to many directions associated with the evolution of data. In some organisations, people are overwhelmed by the hugeness, growing variety and veracity of data generated for business purposes. As a result, many |

| | |
|---|---|
| the challenges that it poses to organisations. Some organisations sit with huge datasets, and they don't know how to refine and use them. Pervaiz et al. (2019) explained that data cleaning is complex, and it requires a substantial amount of effort. Hence, some organisations focus on refining and selling the data (Löfgren & Webster, 2020).<br>The third level is the enabling technologies (Chodak et al., 2020). Technologies are used to generate and store various types of big data (Wang et al., 2020), which make them sources of origin. The technologies include databases and servers. The three levels of origin are transformative to the evolution of data because of the dynamism they incise into the sources and use. | organisations struggle with the analytics (Nyikana & Iyamu, 2022). Thus, some organisations are often challenged on how to steer the use of the data towards competitive advantage. Also, there are concerns regarding the security and privacy of personal data created on various platforms using different devices (Otto, 2022). This could be attributed to the individuals not knowing how their data will be used.<br>Organisations are confused and struggle to differentiate between small data and big data (Nyikana & Iyamu, 2023b). The confusion is attributed to the similarities and overlapping characteristics of these two concepts. This could be due to the many directions the data is taking. (Faraway & Augustin, 2018). |
| **Momentum** | **Type** |
| The speed and variety of data are increasing rapidly, to the point where the enabling technologies (hardware and databases) are struggling to handle the data, in some organisations (Gao et al., 2021). In recent years, the storage capacity of technologies remained a focus, primarily to ensure the growing volume, variety, and veracity are appropriately hosted and used.<br>The momentum of the data evolution has implications for both individuals and organisations (Meadows et al., 2022). For individuals, it requires them to keep pace with the speed (Sestino et al., 2020) and understand how to transform the data, to improve competitiveness. Thus, people must regularly enhance their skills, to know how and when to apply the datasets. This includes designing an architecture for the big data. For organisations, the speed of data evolution is a drive for the advancement in technological systems (Pääkkönen & Pakkala, 2020). This means that organisations must enhance their infrastructure to make sure that they can keep up with the enormous data being generated. | Different types of data such as videos, motions, voice, and images are generated each day (Dash et al., 2019). Often, the data is generated using electronic devices (Lee, 2017). Some of this data is generated in real time, which assists in fast and instant decision-making (Zhang et al., 2020). For example, some people make use of wearable devices which generate data through sensors. This data is used to personalize patients' treatment. Another example is the face-to-face meetings in organisations that are getting less common. Meetings are conducted using online platforms such as Zoom, Microsoft Teams and Google Meet.<br>Adaptability has increasingly become a challenge for many organisations because of the growth and increasing types of data (Sandhu, 2021). Data is everywhere and can be accessed anytime. Organisations such as healthcare are struggling with the storage of data (Salunkhe, 2023). This is due to the policies and governance requiring them to store the data for as long as it is needed. This becomes a challenge on its own because these organisations do not have enough storage for the increasing types of data (Hussien et al., 2021), and they cannot discard the data. This means that policy becomes an important aspect of type. As a result, organisations are redesigning their strategies and processes to be able to adapt and make use of the different types of data (the variety and veracity of data) (Sestino et al., 2020), to enable growth and competitive advantage. |

The analysis tabulated in Table 2 guided, using the dimension of social change from structuration theory, reveals six crucial: (i) adaptive, (ii) advanced technology, (iii) levels of data originality, (iv) transformative (v) agent interaction and (vi) architecture were discovered.

The analysis highlights that the inevitable change from small (traditional) data to big data comes with challenges. One of the influencing factors is associated with the levels (individuals, organisations, and enabling technologies) of originality. Each level comes with unique complex structures and datasets. As a

mitigating factor to the complexity, new infrastructure (technology solution) is required, to enable and support the evolving data effectively. Garoufallou and Gaitanou (2021) argued that the same IT solutions used for small data cannot handle big data. This therefore requires a more advanced technology, which organisations (or enterprises) must adapt to.

The dynamic nature of data generated in many organisations necessitates an adaptive approach, to maintain growth and competitiveness (Mikalef et al., 2020). Consequently, an adaptive approach has to be iterative and to do so, it must be engineered through a transformative process. A transformative process establishes data origins and defines its trajectory, whose momentum can easily be assessed. Also, infrastructure is not a standalone component. Meaning, that for the infrastructure to adapt and be used to enable and support the big data, it is influenced by other factors, such as people and processes (Nyikana, 2023).

Additionally, the data must be transformative, to improve the efficiency and effectiveness of the organisation's operations (Vysotska et al., 2024; Holt, 2021). Thus, both the adaptive approach and transformative process have inseparable implications for people and organisations. For people, skills and knowledge are required. Thus, organisations must invest in the people, to acquire the necessary skills, to facilitate data transformative pursuit (Pesqueira et al., 2020). Also, when people adapt to new IT solutions such as big data architecture, they are governed by the processes, compliance, and rules (Iyamu, 2022). Hence, governance is a crucial component that defines the principles, standards and policies that need to be followed when developing and implementing solutions.

The deployment of small and big data or their evolution enforces the advancement of technologies facilitated by agents, which can be people or technologies. Some of the advanced technologies as agents include cloud computing and artificial intelligence (Misra et al., 2020; Manogaran et al., 2018). The agents have relationships with each other: people-to-people, people-to-technology, and technology-to-technology. According to Giddens (1984), relationships enable interaction between agents and structure (rules and resources). In the context of this study, which is underpinned by the dimension of social change under structuration theory, agents refer to human (non-technical) and technology (technical) entities (Iyamu, 2021). In addition, the interaction between people and technology allows people to offer their specialised knowledge, which contributes towards extracting value from data evolution, for organisational competitiveness.

## Conclusion

The study provides a comprehensive understanding of the evolution of small (traditional) data to big data. The change in data originates from the three levels, individuals, organisations, and technology enablers. The evolution comes with challenges to both organisations and individuals. This is because of the dimensional implications presented by the changes in data. Hence, the study provides an understanding of the factors that manifest in the implications. Six findings were discovered to influence the challenges and implications of data change. The factors are adaptive, advanced technology, levels of originality, agent interaction, transformative, and architecture. These findings can assist organisations in getting a better understanding of how data transforms, the trajectory it's taking and how the speed of this change can be aligned with the organisational processes and operations. For this, the organisations can be able to use the data for competitiveness, innovation and decision-making. Therefore, the findings have theoretical implications for academics and practical implications for organisations. For organisations, the findings can be used to develop guidelines and policies for the implementation of big data. For academics, the paper adds to the body of knowledge as there is limited literature on the use of the dimension of social change as a lens from structuration theory.

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