ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 13 (2026) No. 5, pp. 49-66
DOI:10.33168/JLISS.2026.0504

The Transition from Small Data to Big Data Underpinned by Structuration Theory

Nomawethu Tungela, Wandisa Nyikana, Tiko Iyamu

Faculty of Informatics and Design, Cape Peninsula University of Technology, South Africa

IYAMUT@cput.ac.za

Abstract. The lack of a data evolution framework leads to challenges in understanding how and why traditional (small) data evolves into big data in many organisations. This study aims to develop a data evolution framework for organisations' purposes. Qualitative methods were adopted, involving document analysis, through which literature related to the study was collected. The hermeneutic approach was applied in the analysis, guided by the dimensions of social change from structuration theory as a lens. From the analysis, adaptive, advanced technology, levels of data originality, transformative, agent interaction, and architecture were found to be the vital factors influencing how small data evolves into big data. Also, the evolution and transformation of small to big data has a significant influence on logistics in terms of planning, development and operations. Based on these factors, a data evolution framework was developed. Additionally, attributes of the factors are highlighted in the framework. The proposed data evolution framework has significant implications in gaining insights into how data evolves, towards improving the efficient and effective use of small data and big data in organisations. Despite the comprehension of the study, it has theoretical, practical, and methodological implications from technical and non-technical perspectives for organisations. Non-empirical evidence is a limitation which should be considered for future studies.

Keywords: data evolution, dimensions of social change, small data, big data

1. Introduction

Data has been used in many areas, including production, healthcare, and research, for many decades. According to Qian et al. (2022), small data has a limited amount of data that can be collected using traditional methods, and it contains narrow data types that can easily be managed and analysed (Kitchin & Lauriault, 2015). 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 roots in historical components. Between the 1960s and 1980s, the speed and variety of data increased, which required different approaches for storing and managing data. This change has various implications for both technologists and commercial entities. The evolution continued into the 1970s and 1980s when abstraction and classifications of data were dominant (Navathe, 1992).

As we moved into the 21st century, the evolution of data sped up, and challenges grew in different directions. This increase in data was attributed to the emergence of big data, which is defined by its characteristics known as the 3v's: volume, velocity, and variety (Musukutwa, 2022). 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 increases the chances of people not understanding the use of data because of its complexity, which results in making misleading assumptions (Kitchin, 2014; Kuo & Kusiak, 2019). Organisations encounter 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 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 evolves. 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 challenges in the management of data in many organisations. The rapid increase in big data characteristics makes it difficult to manage data.

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). 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 are ontological assumptions, which triggered this study. The objectives of this paper were therefore to determine the implications of the dimension of data evolution for organisations and to develop a conceptual framework that helps to determine the factors that influence the evolution of small data into big data. This is highly significant primarily because we have not seen the end of data evolution.

Logistics is a process that involves planning, implementation, control and storage of resources such as goods, services, energy and information from the supplier to the customer (Knežević et al., 2025). Logistics focuses on the movement and storage of goods to satisfy customer needs. The management and governance of logistics rely on the use of big data. This makes the transformation of small to big data crucial. For instance, big data is used to understand customer demands and predict market trends (Jahani, Jain & Ivanov, 2023). This helps to make strategic decisions, improve operational efficiency and gain a competitive advantage (Al-Ababneh et al., 2025). 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. The theory helps to understand how data is transformed and used, including the direction it takes over time, as it evolves from small data to big data. The dimension of social change encompasses four cardinal points: Origin, Type, Momentum, and Trajectory, which are concerned with sources, change, pace, and direction, respectively (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.

2. 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 in the analysis, processing, management or interoperability (Sandhu, 2021; Wang et al., 2020), which are often influenced by change, direction, and type of data.

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 the entire data, as well as 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 speed at which data is evolving can be attributed to factors such as value and usefulness for organisations. 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. The formula is intended to guide organisations when selecting big data analytics tools. 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, such as the types, trajectory, and speed at which the data change, within context, which results in organisations not fully benefiting from their data. 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) suggested 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. The challenges include unprecedented volume (Gao et al., 2021), growing types (Dash et al., 2019), and the speed at which data is generated (Goldstein et al., 2021). 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, such as prescriptive, predictive, and diagnostic, 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.

3. Dimension of Social Change

The 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 the 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.

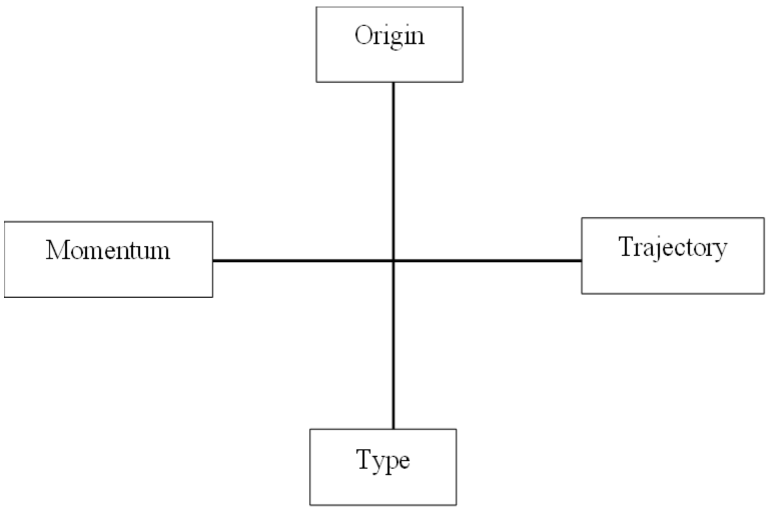

Fig. 1: Dimension of Social Change (Giddens, 1984).

Origin is concerned with establishing the source and history of an episode (Giddens, 1984). This element assists in tracing and examining 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 a 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 implications of the dimensions of data change, tacit knowledge gained from practical consciousness is fundamental. Giddens (1984, p. 23) describes practical consciousness as consisting 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 rationalise 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).

4. 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 that 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 methods (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 were 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 a period (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 back as the year 1950. These were useful documents and contributed to the trajectory of data evolution. 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, AIS, EBSCOhost, and Emerald were consulted to collect the data. These sources host a vast majority of information systems and information technology literature. Also, the sources are the most popular, for access purposes. The material included different types such as journals, books, book chapters and other papers related to the phenomenon under investigation.

Keywords such as data, big data, and data evolution were used to search for the literature. This was to ensure the literature most appropriate to the study was gathered. Severally, the exercise was repeated by the co-authors on separate occasions. In reading through the literature, we observed duplications from focus perspectives. We therefore concluded that the point of saturation has been reached. A total of 74 documents (materials) were collected. After a thorough scrutiny guided by the study's objective, 50 of the materials were found to be most related and appropriate for the study. This was because the materials focused on five different crucial areas, which are definitions, benefits, challenges, architecture, and framework of small data and big data. 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				
Small Data Total	**1**	**7**		**1**
BIG DATA				
Big Data Total	4	33	2	2
Total = 50	**5**	**40**	**2**	**3**

5. Dimension of Social Change: Analysis and Discussion

An analysis of the data was conducted to extract new insights. The hermeneutic approach was employed for the analysis of the data from an interpretivist perspective. 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 a 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 the Dimensions 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). 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. The unrefined data poses challenges 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 requires a substantial amount of effort. Hence, some organisations focus on refining and selling the data (Löfgren & Webster, 2020). 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 makes them sources of origin. The technologies include databases and servers. The three	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 5Vs by including veracity and value (Sandhu, 2021). The evolution is a result of the transformative process and the need for data by individuals and organisations. 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 organisations struggle with the analytics (Nyikana & Iyamu, 2022). Thus, some organisations are often challenged on how to steer the use of the data towards a competitive advantage. Also, there are concerns regarding the security and privacy of the 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. Organisations are confused and struggle to differentiate between small data and big data (Nyikana & Iyamu, 2023b). The confusion is

levels of origin are transformative to the evolution of data because of the dynamism they incise into the sources and use.	attributed to the similarities and overlapping characteristics of these two concepts. This could be due to the many directions the data is taking, which is linked to the characteristics of big data. (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 has remained a focus, primarily to ensure the growing volume, variety, and veracity are appropriately hosted and used. 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 big data. For organisations, the speed of data evolution is a driver for the advancement in technological systems (Pääkkönen & Pakkala, 2020). This means that organisations must enhance their infrastructure to make sure that it 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 personalise 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. 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 the 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.

6. Data Evolution Framework

A subjective approach was employed to identify the factors that influence the evolution of small data into big data, from the analysis tabulated in Table 2. Six influencing factors were found: (i) adaptive, (ii) advanced technology, (iii) levels of data originality, (iv) transformative, (v) agent interaction, and (vi) architecture. The six factors have an impact on the management, governance and strategic planning, and operation of the logistical issues. Based on the factors, a framework (Figure 2) was developed. The framework depicts the connectedness between the influencing factors using arrows. The arrows are captioned with the attributes of the factors. Additionally, the discussion that follows should be read in conjunction with the framework to gain a better understanding of how small data evolves into big data, from a dimension of social change perspective.

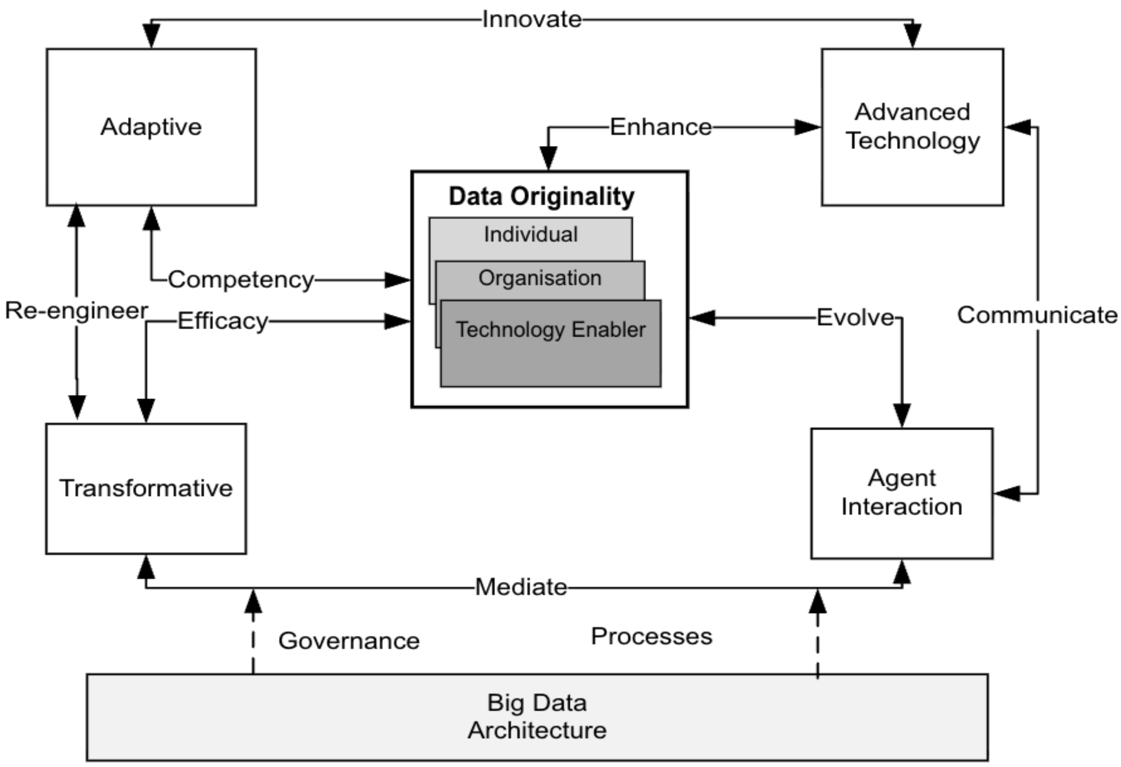

Fig. 1: Factors Influencing the Evolution of Small Data into Big Data

6.1. Adaptive

Adaptivity entails flexibility, the ability to adapt to different approaches or modern solutions. Zakraoui et al. (2019) described adaptive behaviour as the ability to adjust behaviour in a changing environment. The evolution of data, therefore, necessitates adaptation from both technical and non-technical perspectives. From the technical front, as data evolves, it adapts to the IT solutions such as servers, databases, and operating systems in the environment. It is, therefore, crucial to continually advance (innovate) IT solutions to ensure that they are adaptive to the evolution of data. For businesses (non-technical), people's competence is required to employ and manage data as it evolves. This is vital because people take advantage of the evolution of data to re-engineer transformation in the organisations. The dynamic nature of data generated in many organisations necessitates an adaptive approach to maintain growth and competitiveness (Mikalef et al., 2020).

If an environment remains adaptive, it contributes to re-engineering and transformation towards the efficiency and effectiveness of business processes. Kandampully et al. (2021) explained that when an organisation adapts to innovative technologies, business models and processes must be re-engineered to improve sustainability and growth. Re-engineering is also explained by Harika et al. (2021) as a redesigning approach to process, maximise the benefits and sustain competitive pressures (Lopez et al., 2020). The adaptive approach is not static, it must be iterative, and to do so, it must be re-engineered through a transformative process.

6.2. Advanced Technology

The term advanced technology refers to an IT solution that is still in its infant stage but has the potential for significant value within an environment (Nutu, 2021). Advanced technology has impacted and transformed the ways organisations conduct business, including how people (agents) employ it to interact. For example, employees carefully tend to employ advanced technologies such as robotic systems, cloud computing, and augmented reality in conjunction with big data (Ahi et al., 2022). Garoufallou and Gaitanou (2021) argue that the IT solutions used for small data cannot handle big data because they have not been tested or considered mature enough. This could be attributed to the traditional methods that are not equipped to manage huge datasets and analyse the unprecedented variety, veracity, and velocity of data (Bahri et al., 2018).

As a result, the use of advanced technologies to manage data evolution requires an adaptive and innovative approach in an organisation. Also, the deployment of advanced technology must fit into the environmental settings. This is a challenge for organisations that still have legacy systems that are not adaptive to advanced technologies. Therefore, to create an environment that is a recipient of advanced technologies, an innovative process must be ensured.

6.3. Levels of Data Originality

The term levels refer to individuals, organisations, and enabling technologies. They are categorised as levels because of dependence and interrelationships between them: individuals are employed by organisations, and technologies enable organisations to function (Zizic et al., 2022). These levels generate data from small to big data. 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 effectively support the evolving data.

Data evolves quickly and rapidly due to the different electronic devices that are used to provide solutions for day-to-day activities. For example, an individual can generate huge amounts of data by wearing a smartwatch. The smartwatch records the daily activities performed by an individual, such as walking and running distance, stairs climbed and heart rate (Xiao-Yong et al., 2023; Miao et al., 2024). The data generated and recorded from the smartwatch gets sent to the organisation to make informed decisions. An organisation stores and manages the big data generated from individuals using various technology solutions and competencies, including efficacy that can transform the data into a useful purpose. This requires organisations to have enhanced technologies such as cloud computing solutions to store the data (Oussous et al., 2018). When organisations adopt these advanced technologies and employ relevant competence, they increase their sustainability and competitive advantage.

6.4. Data Transformative

Transformative refers to a shift, which is the evolution of small data into big data. Data transformative has implications in many areas, such as effectiveness and type. Data must be transformative, to improve the efficiency and effectiveness of the organisation's operations (Vysotska et al., 2024; Holt, 2021). Data transformation is the process of converting the source data into the desired data type (Lin et al., 2021). Additionally, both the adaptive approach and the transformative process have inseparable implications for people and organisations. Competency is critical; therefore, it requires people with appropriate skills and knowledge to re-engineer the use of data during its evolution for efficient purposes (Holt, 2021). From an organisation's perspective, data transformative influences business goals, objectives, and direction.

Thus, organisations must invest in the people to acquire the necessary skills, to facilitate data transformative (Pesqueira et al., 2020). Another important aspect is that the transformative process is influenced by data origins and defines the trajectory of an organisation. Also, the transformative state determines the momentum at which data evolution is managed to improve business effectiveness. Hence, organisations continue to transform their environments to accommodate changes in data that happen at high speed.

6.5. Agent Interaction

In the context of this study, agents refer to humans and technology (Iyamu, 2021). Gaining understanding and using data in its evolutionary mode requires interactions. The interactions are based on and shaped by relationships between the agents. According to Giddens (1984), relationships enable interaction between agents and structure (such as technology). The interaction is founded on humans employing technology to use data (small data and big data) in organisations. The agents have relationships with each other: people-to-people, people-to-technology, and technology-to-technology. For human agents to gain a better understanding of the roles of advanced technology in data evolution, interaction occurs. Such an understanding mediates processes using technology, including rules of engagement.

The deployment of small data and big data, or their evolution, is facilitated by agents and people employing advanced technologies such as big data analytics and artificial intelligence (Misra et al., 2020; Manogaran et al., 2018). In addition, the interaction between the agents allows people to offer their specialised skills and knowledge, in assessing data transformative and managing potential risks (such as privacy) and benefits (such as value). This increases the value that can be gained from data evolution for organisational competitiveness. Canary and Tarin (2017) state that the day-to-day interactions of the agents transform and reproduce structures. This is a contribution to data evolution in that the interaction between the agents sways the transformation of technologies and improves effectiveness and efficiency.

6.6. Architectural Facet

Architecture is a design of a system that shows the relationship and interaction of the components with each other and how they relate to the environment (Tschoppe & Drews, 2022). The architectural facet is a term to represent the interconnectedness of the factors (adaptive, advanced technology, levels of data originality, transformative, and agent interaction) that influence architectural design. The connectedness reveals the need for governance and processes, which help to address the challenge of traditional data architectures not being able to handle big data. The challenge emanates from huge and complex datasets of big data. As a result, some organisations are redesigning and transforming their architectures to deal with the characteristics of big data, where challenges such as security, overload, and integration often arise (Ruiz et al., 2021). There are different big data architectures that exist, such as lambda, kappa and MapReduce (Barradas et al., 2022; Farooqi et al., 2019).

The adaptation of modern IT solutions, such as big data architecture, requires governance (Iyamu, 2022). Thus, governance is a crucial component of the architectural design. The governance defines the principles, standards and policies for small data and big data, as they evolve. Processes are followed to define how to store, retrieve, access, and manage small data and big data. Also, processes are used to guide the selection and deployment of technologies that enable and support data evolution.

7. Implication of the Study

The study has theoretical, practical, and methodological implications for organisations and academic domains. As shown in Table 3, the implications are embedded in both technical and non-technical factors. The Table focuses on how the factors influence the evolution of small data into big data. which are discussed in section 6.

Table 3. Implications of Data Evolution from Small Data to Big Data

Implication	Technical	Non-technical
Theoretical	From a technical perspective, the framework can be used as a guide to develop the systems that can support the evolving data. However, to use the framework, specialised skills and an understanding of the components of the framework are required. Mikalef et al. (2019) argue that having the appropriate skillset is necessary for those dealing with big data in an organisation. Consequently, this helps the organisations to gain value from the big data.	Employees within the organisation need to understand how to interpret the framework and implement its components. This helps to develop and re-engineer procedures and policies, to improve business sustainability and growth. Ekechi et al. (2024) emphasise the importance of policies and procedures towards shaping the growth of an organisation.

Practical	The evolution of small data to big data requires an organisation to be more innovative and adaptive, to accommodate changing needs. Thus, it requires the use of advanced technology. The systems that were used in small data have to be transformed to be compatible with big data (Garoufallou & Gaitanou, 2021). For instance, Hadoop focuses on distributing file systems, while MapReduce is used to process and store big data (Boumlik & Bahaj, 2018).	Based on the evolution, organisations can develop standards and policies to adopt big data technologies such as analytics methods (Bonesso et al., 2022). Some of the decisions made in organisations are no longer based on experience but on data analytics (Didas et al., 2024), which require training and upskilling to adapt to the technologies.
Methodological	Adopting the framework to integrate both existing systems necessitates a big data architecture. Therefore, employees must understand the step-by-step procedures involved to apply the framework effectively and efficiently. Wang et al. (2018) highlight the importance of an architecture to provide connection and agent interaction of different components for the overall functionality of the system.	The framework needs to comply with the standards, principles, and policies governing big data. it is within such a context that Iyamu (2022) states that the adaptation of modern IT solutions, such as advanced technology, requires governance.

The implications have an impact on decisions at both senior management and other employees, in the business and IT units of an organisation. The theoretical implications highlight new dimensions such as policies, standards, and principles, including skillsets that specifically focus on big data. For example, in practical terms, innovation and adaptive approaches are crucial for many organisations to be flexible and improve competitiveness.

8. Conclusion

This study enhances our comprehension of the interwoven complex interplay of factors influencing the architectural design of big data. By employing dimensions of social change, we identified six essential factors that shape the data evolution process: adaptive, advanced technology, levels of data originality, transformative, agent interaction, and architecture. These factors, including their attributes, highlight the dimensions of change involved in data evolution, emphasising the need for holistic approaches that consider technological, process-oriented, organisational, and human dimensions. The study contributes theoretically and practically. From the theoretical front, the study contributes to the literature on small data and big data in organisations by providing a nuanced perspective on how a framework can be used to gain a deeper insight into data evolution. Additionally, the study shows the utility of structuration theory's dimensions of social change in understanding complex organisational phenomena from a data evolution perspective. The findings of the study are also significant on the logistical issues such as supplier and customer relationship building, delivery delays, and warehouse capacities (Ruzieh et al., 2025).

Practically, our proposed framework suggests that organisations must focus on developing policies, standards, and principles to address the influencing factors and attributes identified. However, the study has limitations, such as focusing on a non-empirical approach. Future research should employ the case study approach to gain from empirical evidence, from both technical and non-technical viewpoints. Additionally, future studies can employ empirical evidence to validate the framework in different organisational contexts.

References

Aboud, A. & Robinson, B. (2022). Fraudulent financial reporting and data analytics: an explanatory study from Ireland. *Accounting Research Journal*, *35*(1), 21–36.

Acciarini, C., Cappa, F., Boccardelli, P. & Oriani, R. (2023). How can organizations leverage big data to innovate their business models? A systematic literature review. *Technovation*, *123*, 102713.

Ahi, A. A., Sinkovics, N., Shildibekov, Y., Sinkovics, R. R. & Mehandjiev, N. (2022). Advanced technologies and international business: A multidisciplinary analysis of the literature. *International Business Review*, *31*(4), 1-17.

Al-Ababneh, H. A., Maiboroda, O., Kukin, I., Yakovets, V. & Hryniv, L. (2025). Big Data Adoption in International Logistics Management. *Journal of Theoretical and Applied Information Technology*, *103*(14), 4951- 4966.

Ali, F., El-Sappagh, S., Islam, S.R., Ali, A., Attique, M., Imran, M. & Kwak, K.S. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. *Future Generation Computer Systems*, 114, 23-43.

Bahri, S., Zoghlami, N., Abed, M. & Tavares, J.M.R. (2018). Big data for healthcare: a survey. *IEEEaccess*, *7*, 7397-7408.

Barradas, A., Tejeda-Gil, A. & Cantón-Croda, R.M. (2022).'Real-time big data architecture for processing cryptocurrency and social media data: A clustering approach based on k-means', Algorithms 15(5), 1–11.

Boje, D. M., Baca-Greif, H., Intindola, M. & Elias, S. (2017). The episodic spiral model: a new approach to organizational processes. *Journal of Organizational Change Management*, *30*(5), 683-709.

Bonesso, S., Gerli, F. & Bruni, E. (2022). The emotional and social side of analytics professionals: an exploratory study of the behavioral profile of data scientists and data analysts. *International Journal of Manpower*, *43*(9), 19-41.Boumlik, A. & Bahaj, M. (2018). Big Data and IoT: A Prime Opportunity for Banking Industry. In: M. Ezziyyani., M. Bahaj., & F. Khoukhi (Eds.), Advanced Information Technology, Services and Systems, 25, pp. 396-407. Springer.

Canary, H. E. & Tarin, C. A. (2017). *Structuration theory*. The international encyclopedia of organizational communication.

Cassell, C. & Bishop, V. (2019). Qualitative data analysis: Exploring themes, metaphors and stories. *European Management Review*, *16*(1), 195-207.

Chodak, G., Suchacka, G. & Chawla, Y. (2020). HTTP-level e-commerce data based on server access logs for an online store. *Computer networks*, *183*, 1-5.

Cockcroft, S. & Russell, M. (2018). Big data opportunities for accounting and finance practice and research. *Australian Accounting Review*, *28*(3), 323-333.

Dash, S., Shakyawar, S.K., Sharma, M. & Kaushik, S. (2019). Big data in healthcare: management, analysis and future prospects. *Journal of big data*, *6*(1), 1-25.

Davenport, T. H. & Dyché, J. (2013). Big data in big companies. *International Institute for Analytics*, *3*, 1-31.

Dawarka, V. & Bekaroo, G. (2022). Building and evaluating cloud robotic systems: A systematic review. *Robotics and Computer-Integrated Manufacturing*, *73*, 102240.

Del-Shamarran, N. (2022). Why Society Change: Anthony Giddens's Structuration Theory and Time-Space Distanciation. *Dekonstruksi*, *7*(01), 183-195.

Dezi, L., Santoro, G., Gabteni, H. & Pellicelli, A.C. (2018). The role of big data in shaping ambidextrous business process management: Case studies from the service industry. *Business Process Management Journal*, *24*(5), 1163-1175.

Dhaliwal, G. & Shojania, K. G. (2018). The data of diagnostic error: big, large and small. *BMJ quality & safety*, *27*(7), 499-501.

Didas, M., Chali, F. & Elisa, N. (2024). The Nexus of Big Data and Big Data Analytics for Managerial Business Decision-Making: A Systematic Review Analysis. *Journal of ICT Systems*, *2*(1), 36-58.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K….. & Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642.

Ekechi, C. C., Chukwurah, E. G., Oyeniyi, L. D. & Okeke, C. D. (2024). A review of small business growth strategies in African economies. *International Journal of Advanced Economics*, *6*(4), 76-94.

ElDahshan, K., Selim, E., Ebada, A.I., Abouhawwash, M., Nam, Y. & Behery, G. (2022). Handling Big Data in Relational Database Management Systems. *CMC- Computers Materials & Continua*, *72*(3), 5149-5164.

Faraway, J.J. & Augustin, N.H. (2018). When small data beats big data. *Statistics & Probability Letters*, *136*, 142-145.

Farooqi, M.M., Shah, M.A., Wahid, A., Akhunzada, A., Khan, F., ul Amin, N. et al., (2019), 'Big data in healthcare: A survey', in F. Khan (ed.), Applications of intelligent technologies in healthcare, 143–152, Springer, Switzerland AG.

Gao, R.X., Wang, L., Helu, M. & Teti, R. (2020). Big data analytics for smart factories of the future. *CIRP annals*, *69*(2), 668-692.

Garoufallou, E. & Gaitanou, P. (2021). Big data: opportunities and challenges in libraries, a systematic literature review. *College & Research Libraries*, *82*(3), 410.

Gil, D., Johnsson, M., Mora, H. & Szymański, J. (2019). Review of the complexity of managing big data of the internet of things. *Complexity*, *2019*, 1-12.

Giddens, A. (1984). *The Constitution of Society: Outline of the Theory of Structuration*. 1st ed. University of California Press.

Goldstein, I., Spatt, C.S. & Ye, M. (2021). Big data in finance. *The Review of Financial Studies*, *34*(7), 3213–3225.

Gravetter, F.J. & Forzano, L.A.B. (2018). *Research methods for the behavioral sciences*. 6th ed. Cengage learning.

Grover, V., Chiang, R. H., Liang, T. P. & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, *35*(2), 388-423.

Harika, A., Sunil Kumar, M., Anantha Natarajan, V. & Kallam, S. (2021). Business Process Reengineering: Issues and Challenges. In: D. Goyal., P. Chaturvedi., A. K. Nagar., & S. Purohit (Eds.), *Proceedings of Second International Conference on Smart Energy and Communication. Algorithms for Intelligent Systems*, (pp. 363-382). Springer.

Hassan, M.K., El Desouky, A.I., Elghamrawy, S.M. & Sarhan, A.M. (2019). Big data challenges and opportunities in healthcare informatics and smart hospitals. In A. E. Hassanien., M. Elhoseny., S. H. Ahmed., & A. K. Singh (Eds.), *Security in smart cities: Models, applications, and challenges*, (pp. 3-26). Springer.

Holt, V. (2021). Obtain a Ph. D. and a career in data. *Communications of the ACM*, *64*(7), 7-7.

Hughes, G., Shaw, S. E. & Greenhalgh, T. (2022). Why doesn't integrated care work? Using Strong Structuration Theory to explain the limitations of an English case. *Sociology of Health & Illness*, *44*(1), 113-129.

Hussein, A. A. (2020). How many old and new big data v's characteristics, processing technology, and applications (bd1). *International Journal of Application or Innovation in Engineering & Management*, *9*(9), 15-27.

Hussien, H.M., Yasin, S.M., Udzir, N.I., Ninggal, M.I.H. & Salman, S. (2021). Blockchain technology in the healthcare industry: Trends and opportunities. *Journal of Industrial Information Integration*, *22*, 1-23.

Iyamu, T. & Nyikana, W. 2024. Activity theory view of big data architectural design for enterprises. *Journal of Information Systems Engineering and Management*. 9(3), 1-15.

Iyamu, T. (2023). *Advancing Big Data Analytics for Healthcare Service Delivery*. 1st ed. Taylor & Francis.

Iyamu, T. (2022). *Enterprise Architecture for Strategic Management of Modern IT Solutions*. 1st ed. Auerbach Publications.

Iyamu, T. (2021). The Role of African Proverbs in Advancing Information Systems Research. *The African Journal of Information Systems*, *13*(4), 475-492.

Iyamu, T. (2019). The architectures of data and information: Their confounded confusion. *South African Journal of Information Management, 21*(1), 1-9.

Iyamu, T., Nehemia-Maletzky, M. & Shaanika, I. (2016). The overlapping nature of business analysis and business architecture: What we need to know. *Electronic Journal of Information Systems Evaluation*, *19*(3), 169-179.

Jahani, H., Jain, R. & Ivanov, D. (2023). Data science and big data analytics: a systematic review of methodologies used in the supply chain and logistics research. *Annals of Operations Research*, 1-58.

Jones, M. (2019). What we talk about when we talk about (big) data. *The Journal of Strategic Information Systems*, *28*(1), 3–16.

Kandampully, J., Bilgihan, A., Bujisic, M., Kaplan, A., Jarvis, C. B. & Shukla, Y. (2021). Service transformation: How can it be achieved? *Journal of Business Research*, *136*, 219-228.

Kendrick, C. (1961). Estimation of Service Requirements for Production Purpose. *International Journal of Production Research*, *1*(1), 1-12.

Kitchin, R. & McArdle, G. (2016). What makes Big Data, Big Data? Exploring the ontological characteristics of 26 datasets. *Big Data & Society*, *3*(1), 1-10.

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*.1st ed. Sage.

Knežević, I., Mandžuka, B., Tomašić, D. & Ćelić, J. (2025). The Role of Digital Tools in Logistics Decision-Making: An Overview of Tools, Benefits and Challenges. *Transportation Research Procedia*, *91*, 377-384.

Kuo, Y. H. & Kusiak, A. (2019). From data to big data in production research: the past and future trends. *International Journal of Production Research*, *57*(15-16), 4828-4853.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business horizons*, *60*(3), 293-303.

Li, X., Liu, D., Sun, J. & Zhu, Z. (2022). Challenges of industrial engineering in big data environment and its new directions on extension intelligence. *Procedia Computer Science*, *214*, 1561-1567.

Lin, Z., Chi, J., Jianqiao, S., Weifeng, W. & Fengjuan, B. (2021, December 2-4). *Research on Heterogeneous Data Transfer Method for Power Energy Management*. In 2021 5th International Conference on Power and Energy Engineering (ICPEE), Xiamen, China.

Löfgren, K. & Webster, C.W.R. (2020). The value of Big Data in government: The case of 'smart cities'. *Big Data & Society*, *7*(1), 1-14.

Lopez-Arredondo, L. P., Perez, C. B., Villavicencio-Navarro, J., Mercado, K. E., Encinas, M. & Inzunza-Mejia, P. (2020). Reengineering of the software development process in a technology services company. *Business Process Management Journal*, *26*(2), 655-674.

Manogaran, G., Varatharajan, R., Lopez, D., Kumar, P.M., Sundarasekar, R. & Thota, C. (2018). A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system. *Future Generation Computer Systems*, *82*, 375–3 87.

McAfee, A. & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, *90*(10), 61-67.

Meadows, M., Merendino, A., Dibb, S., Garcia-Perez, A., Hinton, M., Papagiannidis, S., Pappas, I. & Wang, H. (2022). Tension in the data environment: How organisations can meet the challenge. *Technological Forecasting and Social Change*, *175*, 1-11.

Meneghello, J., Thompson, N., Lee, K., Wong, K. W. & Abu-Salih, B. (2020). Unlocking social media and user generated content as a data source for knowledge management. *International Journal of Knowledge Management (IJKM)*, *16*(1), 101-122.

Miao, F., Wu, D., Liu, Z., Zhang, R., Tang, M. & Li, Y. (2023). Wearable sensing, big data technology for cardiovascular healthcare: current status and future prospective. *Chinese Medical Journal*, *136*(09), 1015-1025.

Mikalef, P. & Krogstie, J. (2020) Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, *29*(3), 260-287.

Misra, N.N., Dixit, Y., Al-Mallahi, A., Bhullar, M.S., Upadhyay, R. & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of things Journal*, *9*(9), 6305-6324.

Murthy, C.V.B., Shri, M.L., Kadry, S. & Lim, S. (2020). Blockchain based cloud computing: Architecture and research challenges. *IEEE access*, *8*, 205190-205205.

Navathe, S. B. (1992). Evolution of data modelling for databases. *Communications of the ACM*, *35*(9), 112-123.

Nigar, N. (2020). Hermeneutic phenomenological narrative enquiry: A qualitative study design. *Theory and Practice in Language Studies*, *10*(1), 10-18.

Nutu, C.S. (2021). Perspectives on advanced and basic engineering technologies. *Scientific Bulletin of Naval Academy*, *1*, 83-87.

Nyikana, W. (2023). *The architectural design of big data for business enhancement in enterprises* [Master's thesis, Cape Peninsula University of Technology]. Google Scholar

Nyikana, W. & Iyamu, T. (2023c). The logical differentiation between small data and big data. *South African Journal of Information Management*, *25*(1), 1-9.

Nyikana, W. & Iyamu, T. (2023, March 11-13). *The taxonomical distinction between the concepts of small data and big data*. In Proceedings of the 16th International Association for Development of Information Society, Lisbon, Portugal.

Nyikana, W. & Iyamu, T. (2023a). A Formulaic Approach for Selecting Big Data Analytics Tools for Organizational Purposes. In Z. Sun (Ed.), *Handbook of Research on Driving Socioeconomic Development with Big Data*, (pp. 224-242). IGI Global.

Nyikana, W. & Iyamu, T. (2022, January 4-7). *A Guide for Selecting Big Data Analytics Tools in an organisation*. In Proceedings of the 55th Hawaii International Conference on System Sciences, Maui, Hawaii.

Otto, B. (2022). The evolution of data spaces. In *Designing data spaces: The ecosystem approach to competitive advantage* (3-15). 1st ed. Springer International Publishing.

Oussous, A., Benjelloun, F. Z., Lahcen, A. A. & Belfkih, S. (2018). Big Data technologies: A survey. *Journal of King Saud University-Computer and Information Sciences*, *30*(4), 431-448.

Pääkkönen, P. & Pakkala, D. (2020). Extending reference architecture of big data systems towards machine learning in edge computing environments. *Journal of Big Data*, *7*, 1-29.

Pervaiz, F., Vashistha, A. & Anderson, R. (2019, July 3-5). *Examining the challenges in development data pipeline*. In Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies, New York, USA.

Pesqueira, A., Sousa, M. J. & Rocha, Á. (2020). Big data skills sustainable development in healthcare and pharmaceuticals. *Journal of Medical Systems*, *44*, 1-15.

Qian, C., Huang, B. Yang, X., & Chen, G. (2022). Data science for oceanography: from small data to big data. *Big Earth Data*, *6*(2), 236-250.

Ranjan, J. & Foropon, C. (2021). Big data analytics in building the competitive intelligence of organizations. *International Journal of Information Management*, *56*, 1-13.

Rattan, A.K. (2018). Data integrity: history, issues, and remediation of issues. *PDA Journal of Pharmaceutical Science and Technology*, *72*(2), 105-116.

Ravikumar, T., Sriram, M. & Murugan, N. (2022, October 13-14). *Applications and Risks of Big Data in Financial Services*. In Proceedings of 10th International Conference on Emerging Trends in Corporate Finance and Financial Markets, Mysore, India.

Ruiz, M. D., Gómez-Romero, J., Fernandez-Basso, C. & Martin-Bautista, M. J. (2021). Big data architecture for building energy management systems. *IEEE Transactions on Industrial Informatics*, *18*(9), 5738-5747.

Ruzieh, A. S., Awwad, B. S. & Razia, B. S. (2025). Review of logistics challenges within the construction industry. *EuroMid Journal of Business and Tech-Innovation*, 4(1), 1-22.

Salunkhe, V. (2023). Secure sharing of healthcare data using a decentralized blockchain network for the Internet of Medical Things (IoMT). *International Journal of Computing and Digital Systems*, *14*(1), 1-30.

Sandhu, A.K. (2021). Big data with cloud computing: Discussions and challenges. *Big Data Mining and Analytics*, *5*(1), 32-40.

Schleidgen, S., Friedrich, O., Gerlek, S., Assadi, G. & Seifert, J. (2023). The concept of “interaction” in debates on human–machine interaction. *Humanities and Social Sciences Communications*, *10*(1), 1-13.

Sestino, A., Prete, M.I., Piper, L. & Guido, G. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. *Technovation*, *98*, 1-9.

Shaanika, I. & Iyamu, T. (2020). The use of mobile systems to access health care big data in the Namibian environment. *The Electronic Journal of Information Systems in Developing Countries*, *86*(2), 1-15.

Sovacool, B. K., Axsen, J. & Sorrell, S. (2018). Promoting novelty, rigor, and style in energy social science: Towards codes of practice for appropriate methods and research design. *Energy research & social science*, *45*, 12-42.

Taherdoost, H. & Madanchian, M. (2023). Artificial intelligence and sentiment analysis: A review in competitive research. *Computers*, *12*(2), 37.

Thinyane, M. (2017, June 12-13). *Investigating an Architectural Framework for Small Data Platforms*. In Data for societal challenges-17th European Conference on Digital Government. Lisbon, Portugal.

Thirsk, L. M. & Clark, A. M. (2017). Using qualitative research for complex interventions: The contributions of hermeneutics. *International Journal of Qualitative Methods*, *16*(1), 1-10.

Tsang, E. W. (2014). Case studies and generalization in information systems research: A critical realist perspective. *The Journal of Strategic Information Systems*, *23*(2), 174-186.

Tschoppe, N. & Drews, P. (2022, January 4-7). *Developing Digitalization Strategies for SMEs: A Lightweight Architecture-based Method*. In Proceedings of the 55th Hawaii International Conference on System Sciences, Maui, Hawaii.

Tümen-Akyildiz, S.T. & Ahmed, K.H. (2021). An overview of qualitative research and focus group discussion. *International Journal of Academic Research in Education*, *7*(1), 1-15.

Tungela, N., Mutudi, M. & Iyamu, T. (2018, October 3-5). *The roles of e-government in healthcare from the perspective of structuration theory*. In Proceedings of 2018 Open Innovations Conference, Johannesburg, South Africa.

Vysotska, V., Kyrychenko, I., Demchuk, V. & Gruzdo, I. (2024, April 12-13). *Holistic Adaptive Optimization Techniques for Distributed Data Streaming Systems*. In 8th International Conference on Computational Linguistics and Intelligent Systems, Lviv, Ukraine.

Wang, J., Yang, Y., Wang, T., Sherratt, R.S. & Zhang, J. (2020). Big data service architecture: a survey. *Journal of Internet Technology*, *21*(2), 393-405.

Wang, Y., Kung, L. & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological forecasting and social change*, *126*, 3–13.

Xiao-Yong, C. H. E. N., Bo-Xiong, Y. A. N. G., Shuai, Z. H. A. O., Jie, D. I. N. G., Peng, S. U. N. & Lin, G. A. N. (2023). Intelligent health management based on analysis of big data collected by wearable smart watch. *Cognitive Robotics*, *3*, 1-7.

Yokoyama, K. (2010). The Patterns of Change in Higher Education Institutions: The context of the changing quality assurance mechanisms in England, Japan, and New York State. *Tertiary Education and Management*, *16*, 61-80.

Zakraoui, J., Saleh, M. & Al Ja'am, J. (2019). Text-to-picture tools, systems, and approaches: a survey. *Multimedia Tools and Applications*, *78*, 22833-22859.

Zhang, Y., Chen, G., Du, H., Yuan, X., Kadoch, M. & Cheriet, M. (2020). Real-time remote health monitoring system driven by 5G MEC-IoT. *Electronics*, *9*(11), 1-17.

Zhu, H., Madnick, S. E., Lee, Y. W. & Wang, R. Y. (2014). *Data and Information Quality Research: Its Evolution and Future*. 3rd Taylor & Francis Group.

Zizic, M. C., Mladineo, M., Gjeldum, N. & Celent, L. (2022). From industry 4.0 towards industry 5.0: A review and analysis of paradigm shift for the people, organization and technology. *Energies*, *15*(14), 5221.