Artificial intelligence technology to enhance data quality management practices in the banking industry in South Africa

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Received: 7 March 2024
Accepted: 30 August 2024

Data generated and used for decision-making in the banking sector has enabled the industry to overcome different challenges and gain insights to improve customer satisfaction. The importance of high-quality data in the banking industry is imperative to reduce fraud and financial crimes, and to enhance financial decision-making. It is therefore important that good data quality management practices are adopted to secure the stability of financial organisations. The purpose of the research as a concept paper was to propose a conceptual framework for utilising artificial intelligence (AI) technology for data quality management. This study explored the components of a proposed conceptual framework for the utilisation of AI technology for data quality management in the banking sector. In applying a qualitative desktop review, the hourglass model for AI governance and the Data Management Association (DAMA) model was used to develop a proposed conceptual framework relevant to the banking industry. Themes included in the proposed conceptual framework related to legislation and regulations, principles and guidelines, people, strategy, and technology/systems. The literature review's results showed that in South Africa, limited legislation and guidelines are available to support and advance the use of AI in data quality management. It is envisaged that the proposed conceptual framework will provide a reference point to further explore this topic.

Keywords: banking sector, data quality management, artificial intelligence, quality management practice, South Africa

1 Introduction

Data have become a valuable resource for any organisation and are used for analytics and to improve business processes and offerings that a specific organisation provides. This has been no different for the banking sector, where large amounts of data are generated and used for decision-making (Hassan, Popp & Olah 2020:2). Hill (2018) explains that data play a crucial role in reducing fraud and financial crimes and enhanced decision-making. Therefore, as with other industries, the effective management of data in the banking sector is imperative. Towards improving data management practices, the banking sector has adopted artificial intelligence (AI) technology to gain a competitive advantage. AI is used to improve decision-making activities by ensuring that fit for purpose data are readily available for a better customer experience, as well as to enhance customer satisfaction and promote customer retention (Shakina, Shirokaya & Tochilova 2021).

When exploring the meaning of the term AI, Gartner (2016) provides the following description:

> *Artificial intelligence is technology that mimics human performance by learning, drawing its own conclusions, understanding complex content, engaging in dialogues with people and enhancing human cognitive performance or replacing humans in the execution of non-routine tasks.*

Linked to the above definition, as well as descriptions by authors such as Rai, Constantinides and Sarker (2019), AI can be described as the ability of a machine to perform cognitive functions mostly associated with humans. Similarly, Tagliaferri et al. (2020:1) explain that AI can be referred to as computational technologies that imitate mechanisms of human intelligence, such as thought, engagement and sensory understanding. Smith and Nobanee (2020:1) argue that the focus of AI is on using technology to allow for better, more efficient, and more sustainable decision-making by removing human bias from business. It is believed that the removal of this bias will promote business development and reduce margins of error in data quality and automation, to promote accountability and transparency.

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Within the context of the banking sector, AI technology is used to discover suspicious activities such as fraud and to support investigators in gathering evidence about questionable financial activities (Skoller 2020:3). In addition to fraud prevention, Cidon, Gavish and Perone (2019:5) mention that AI technology is also used to track traditional data (this refers to structured data) and other data sources (unstructured data), which may be useful in enhancing the experience of customers and employees in the banking sector. For example, AI technology is useful in protecting personal data to prevent cyber threats, making AI technology valuable as part of high-quality security systems for banks (Soni 2019:6). AI is also able to process huge amounts of data to draw identifiable patterns in the data that humans may not necessarily be able to identify (Kuzlu, Fair & Guler 2021). Furthermore, AI technology can be adopted to improve data quality management activities and, in turn, ensure that data being used for analytics are fit for purpose, with fewer or even no data quality issues, which will improve decision-making processes within the banking industry.

Within the context of the value that AI can offer to the banking sector, the focus of this article is on proposing a conceptual framework that the banking industry in South Africa can use to expand the value of utilising AI-driven technology. The emphasis is specifically on promoting data quality management practices, referring to the practices required to ensure the use of high-quality information throughout the process of handling data (Bauman 2022). Linked to existing models, concepts will be identified and proposed in line with a detailed literature review, to guide the creation of a conceptual framework that can be used in the banking industry to ensure the effective management of data quality. It is important to obtain insight into the components that should be part of the conceptual framework, aimed at ensuring effective data quality management in the banking sector.

2 Contexualising the problem

Large quantities of data are produced and received within organisations such as banks. Such data need to be managed adequately for analytics and decision-making purposes. Having accurate and complete data helps to reduce fraud and financial crimes and enhances financial decision-making (Khan, Indulska & Sadiq 2019). Bauman (2022) states that data quality management focuses on the identification of context-specific processes to improve the relevance and accuracy of data being used for analysis and decision-making. Good practices of data quality management are required to build a solid foundation for all business initiatives, as data quality management provides a framework for business units in an organisation to enforce rules for data use.

It is thus important to ensure that data are successfully managed, so that decisions based on that data are accurate (Azizzadeh et al. 2022). However, effective decision-making and the use of data for organisational progress are only as good as the practices used to manage the quality of the actual data. Because of poor data quality management, organisations such as banks often produce incorrect data, which impacts negatively on the functions of the organisation. This may result in the unnecessary waste of time and human resources to assess the quality of data to ensure that it is fit for purpose. This is evident in numerous studies that emphasise the importance of data quality management in the banking industry, by authors such as Bakar, Razali and Jambari (2021), Azizzadeh et al. (2022), Central Bank of Oman (2022) and Perera and Marikkar (2023). Findings presented in studies by the above authors accentuate the importance of establishing processes and rules to ensure data quality management. Hurkat (2021) mentions that effective and efficient data quality management in financial institutions is a critical challenge to ensure that organisations can perform sophisticated validation checks. The question that one has to ask is how such data quality management can be ensured. di Summa, Reno, Dibari, Pernisco, Sacco and Stella (2022) propose that new AI tools be used to assist with assessing data quality. Perera and Marikkar (2023) argue that AI technology will allow for seamless and timely data quality management, which will result in the reduction of risks and exposures, an increase in revenue, decreases in operational costs, thorough forecasting, and improved customer experience.

However, Musk (2021) states that it may be necessary to carefully consider some regulatory oversight to make sure that AI is utilised to the advantage of organisations and the individuals they serve. Challenges that have been identified with the use of AI technology in the banking sector include adopting stringent privacy regulations and policies, adopting tighter compliance and regularity scrutiny, use of AI technology for harm and the possible loss of jobs due to AI carrying out most of the work that is done by individuals at present (North 2018). On the other hand, AI technology can and should be used for providing accurate and reliable information that can advance decisions (Svoboda 2023). Supporting decision-making requires of AI technology to have access to quality data that is fit for purpose. Therefore, it is imperative that AI technology is used appropriately to manage data quality from a broader ethical and legal perspective. Towards establishing a foundation for the effective use of AI in data quality management, the authors propose the creation of a conceptual framework. The aim of this framework is to allow for synergy between systems, people, and regulations, and in turn mitigate risks and challenges embedded in the use of AI to promote data quality management. Data management legislative and regulatory practices and AI-specific guidelines need to be established as part of a conceptual framework to manage data quality by making use of AI technology. As a concept document, this article explores the development of such a conceptual framework that can be used to improve data quality management practices in the banking industry.

3 Theoretical underpinnings

Towards proposing a conceptual framework for the use of AI in data quality management, scholars such as Ravitch and Riggan (2012: xiv) and Ngulube, Mathipa and Gumbo (2015:61) opine that the foundation of a conceptual framework should be existing theories or models that can be aligned to the key research topic. Concepts drawn from models assist in devising a holistic understanding of key information that informs and is important in constructing the answers to research questions. Thus, the aim of considering relevant theories and/or models is to assist the researcher in identifying key concepts that can be used towards the establishment of a conceptual framework (Grant & Osanloo 2014:13).

Based on the analysis of several models, two models were selected to explore the question on the concepts that should be included in a conceptual framework to ensure the effective use of AI to promote data quality management. These models are the hourglass AI model and the data quality management body of knowledge, developed by DAMA International(2017). The choice of components from the two models provided relevant concepts to create a conceptual framework for the use of AI in data quality management.

The hourglass model of AI governance was selected for the study, as it encapsulates all the elements required to establish an information governance framework for using AI for data quality management. According to Tukia (2022:28), this model depicts the flow of governance requirements from top to bottom and highlights the complexity of AI technology. Seppälä, Birkstedt and Mäntymäki (2021) explain that the hourglass is a metaphor for the flow of grains of sand (environmental layer) through the middle of the hourglass (translation process). The hourglass model for AI governance includes three layers, namely the environmental layer, the organisational layer, and the AI systems layer.

The environmental layer of the AI hourglass framework refers to hard law, principles and guidelines that should be considered in the use of AI to manage data quality and stakeholder pressure (Mäntymäki et al. 2022). Ramírez and Selsky (2016) explain that hard laws (normative regulations) are binding regulations for organisations that make use of AI technology. Principles and guidelines are regulatory documents that are drafted by researchers and accepted by organisations to regulate AI. Such principles and guidelines give detail on, for example, AI ethical guidelines (Hagendorff 2020:109; Thiebes, Lins & Sunyaev 2021:451). It is important that the laws and regulations that govern the use of AI technology are explored to ascertain how best to establish a conceptual framework for using AI for data quality management. Sound AI laws and regulations are required to ensure that best practices are adopted. The last component of the environmental layer refers to stakeholder pressure. Since AI is in its infancy, there is stakeholder pressure on managing its development and use. Stakeholders' awareness of AI management is restricted (Mäntymäki et al. 2022) and, therefore, it is important that stakeholder awareness is assessed, to establish additional interventions required to enhance understanding. Expanding understanding of AI management calls for organisations to integrate AI into their strategies to specify how AI will be used and what business objectives it will help the organisation to achieve (Eitel-Porter 2021:73). Commitment from management and staff is necessary to increase awareness on the implementation and use of AI in data quality management (Schneider et al. 2020:234).

The second organisational layer is focused on value alignment. This requires the alignment between organisational values and AI ethics and ensures that AI is adopted and employed to the benefit of the organisation. Because value-driven practices and ethical decisions are rarely black and white, organisations must handle trade-offs and conflicts, such as those between efficiency and privacy protection (Whittlestone et al. 2019:199). This makes it crucial to articulate the organisation's risk tolerance for adopting AI technology for data quality management practices. The development, use and management of AI systems fall within the third layer, namely the AI systems layer. This layer encompasses detail on the requirements from the environmental and organisational layer necessary to design an AI system that can ensure an effective quality data management process. The AI systems layer is complex because of the difficulty in successfully integrating functional AI as part of quality data management.

To expand the detail required to incorporate AI within a quality data management framework, attention was also given to the data management body of knowledge (DAMA) model. This model provides detail on policies and practices required to ensure the effective management of data quality (Chamberlain 2013:9). Policies and practices are needed to regulate and coordinate the operational aspects of quality data management. The primary goal of policies and practices is to extract value from data, to monetise data and to satisfy regulatory reporting and compliance obligations (Trom & Cronje 2020). According to Kim and Cho (2018:39), policies and practices are needed for standardisation, defining of stakeholder roles and the establishment of practices to ensure effective quality data management. As per the Basel Committee on Banking Supervision (BCBS 239), standards as part of practice guidelines are necessary for organisations to meet regulatory compliance. Orgeldinger (2018:67) and Engels (2019:221) explain that the DAMA (2017) underlines the importance of policies and practices inclusive of standards as a core requirement for quality data management. The DAMA provides foundational information for actions to be executed to ensure quality data management (Murti et al. 2018:161). This includes best practices for data quality management, ongoing quality assurance measures to consider as data changes over time, and analysis criteria that can be applied to ensure that data of the best quality that are fit for purpose are retained (Ehrlinger & Wöß 2017:19). The proposed quality data management processes aim to support best practices to measure, monitor, control, and report on the quality of data available in an organisation. It includes inspection and a control process to monitor data quality and to ensure that tracking and monitoring of data occur in line with defined data quality service level agreements (DAMA 2017).

Based on the information on the hourglass model and the DAMA briefly described in the section above, it can be concluded that a conceptual framework for the utilisation of AI technology to promote quality data management should encompass legislative and regulatory information, as well as the consideration of policies and standards linked to the external and internal organisational environments. Stakeholders should be considered, as well as the processes of managing data quality throughout the life cycle of the data. Ultimately the AI technology should be available to support and assist in ensuring quality data as an asset to an organisation. Key components that could be extracted from the two models towards the development of a conceptual framework for the use of AI in data quality management include:

- legislations and regulations
- principles and guidelines
- people
- strategy
- technology

4 Methodological contexualisation

Aligned to the intent of the research to develop a framework for utilising AI technology in data quality management with emphasis on the South African banking sector, an interpretivist research approach was adopted. Interpretivists aim to gain in-depth understanding of multiple realities, and often adopt a qualitative research approach, which involves the subjective study of reality. A qualitative approach aims to study a phenomenon in an iterative and flexible manner (Thanh & Thanh 2015) and involves reasoning from general to more specific assumptions (Davis 2014b:121).

Within the context of this research, a systematic literature review was used to present a proposed framework for the use of AI to enhance data quality management in the banking sector of South Africa. A systematic literature review is defined as an examination of the evidence pertaining to a precisely stated question that employs explicit and methodical techniques to find, evaluate and critically assess pertinent primary research and extract data from existing literature (Armstrong et al. 2008). According to Lame (2019), a systematic literature review combines scientific evidence to confirm that the quality of the evidence responds to research questions in an open, replicable manner. Related to the research, the key question that was explored was: "What components should be included in a conceptual framework aimed at promoting the use of AI to ensure quality data management within the South African banking industry?"

The qualitative approach was adopted to collect non-empirical data from a variety of existing information sources. Using the rationale for the qualitative approach, which is exploratory by nature, the aim was to attain both meaning and truth related to the phenomenon of proposing a conceptual framework that can be used to ensure the effective application of AI technology in quality data management. Within the above context, the aim of this article is to propose a framework for the use of AI to manage data quality in the banking sector.

5 Systematic literature review

The systematic literature review focuses on searching for answers related to the key research question. It follows a clearly defined plan to comprehensively search through multiple databases to obtain detail related to the research question. The systematic literature review helps to assess existing knowledge and identify categories that, in the case of this research, inform the conceptual framework needed to ensure effective quality data management, by using AI technologies in the banking sector. During the execution of the systematic literature review, databases such as EBSCOhost, Web of Science, Google Scholar, and Scopus were accessed to obtain literature on themes that were identified in the model analysis. These included legislation and regulations, principles and guidelines, people, strategy, and technology. Findings were obtained pertaining to the legislation and regulations that have an impact on using AI technology to enhance data quality management practices in the banking industry in South Africa, referred to the Commission on the Fourth Industrial Revolution (commission), the Protection of Personal Information Act and the international regulations on general data protection.

In South Africa, President Ramaphosa established a Commission on the Fourth Industrial Revolution (4IR) in 2019 to promote national advancement in technology (Government Gazette 2018). South Africa, along with the other initial BRICS nations, namely Brazil, Russia, India, and China, is embracing 4IR technologies, including AI applications in various sectors (BusinessTech 2019). Findings of the commission indicate that a balance is necessary in the use of AI to advance the social, economic, and cultural activities of the country. Opportunities exist for infrastructure development to expand the use of AI in industries, but these are reliant on expanding ICT infrastructure and resources. In order to equip South African citizens and organisations to embrace AI, attention must be paid to the development of foundational and competency skills to advance critical thinking, decision-making and cognitive flexibility. In addition, regulations such as the General Data Protection Regulation (GDPR) (2016/679) composed and accepted in the European Union and the Protection of Personal Information Act (POPIA) (2013) in South Africa, aim to protect individuals' privacy rights in the digital age. The legislation and regulations have implications for quality data management practices in sectors like banking, to ensure that data are protected and not freely used by AI technology. In addition, the banking sector in South Africa must also adhere to standards such as the BCBS (Asamba 2019). The aim of the standards is to provide principles for effective risk data aggregation and reporting. The BCBS provides broad supervisory standards and guidelines and recommends best practices in banking supervision.

As per the BCBS guidelines, risk aggregation and reporting on quality data management requires that key data principles and guidelines be established (Asamba 2019). Data principles and guidelines provide guidance for data creation, acquisition, storage, security, quality, and the use of this data within organisations (Alhassan 2019). These principles and guidelines communicate the objectives, accountabilities, roles, responsibilities, and data retention periods to ensure standardised practices (Morabito 2015). Establishing principles and guidelines for effective data quality management ensures that there is consistency in the manner in which data are managed within an organisation (Kim & Cho 2017). Ryan and Stahl (2021:65) state that principles should be drafted that encompass detail on transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom autonomy, trust sustainability and dignity solidarity. These principles should guide the application and use of AI to ensure quality data management within any organisation. Based on these principles, Al-Ruithe and Benkhelifa (2017) suggest that strategies should be composed to outline high-level actions, aligned with business objectives, a vision statement, business case, long-term and short-term objectives, and an implementation roadmap for the management of data quality activities. The need for alignment between strategies and principles is important, as argued by Alhassan (2019) since it will influence the adoption of AI towards data quality management in the banking sector. Adopted strategies will in turn impact on the people who are assigned various roles in ensuring that data quality management activities are successfully implemented.

Establishing roles and accountabilities while setting guidelines and standards aligned with company strategy is imperative to ensure alignment between organisational strategies and people involved in the execution of such strategies (Weber, Otto & Osterle 2009). Individual roles may vary depending on an organisation’s maturity in data management practices. Roles may include data ownership, stewardship, and committee activities. Employees as data owners should engage in ensuring that standards are executed in line with approved principles and practices (Cheong & Chang 2007). Committees are required to ensure organisation-wide governance, balancing stakeholder interests with standardised data quality management practices (Otto 2011).

Pertaining to the last component identified from the model analysis, AI technology is necessary to maintain and ensure the accuracy of quality data management practices. In the banking industry of South Africa, leveraging AI technology infrastructure can revolutionise data quality management practices (Matsepe & Van der Lingen 2022). Machine learning algorithms automate data cleansing normalisation, and validation can be used to ensure high accuracy and integrity across a variety of datasets (Hubert & Elisha 2023). Natural language processing may be used to extract insights from unstructured data sources that an organisation needs for decision-making. AI-powered predictive analytics facilitates real-time monitoring, enabling banks to swiftly address emerging data quality challenges and uphold regulatory compliance standards (Khan 2023).

6 Proposing a conceptual framework

A conceptual framework is regarded as the result of combining several related concepts to explain or predict a given event, or to provide a broader understanding of the phenomena involved in a research problem (Sitwala 2014:189). Designing a conceptual framework is an inductive process whereby small individual pieces are joined together to contextualise a bigger map of possible relationships between legislation and regulations, principles and guidelines, people, strategy, and technology as components extracted from the selected models. A conceptual framework, based on such components may provide a data quality management cycle necessary for meeting business requirements, creating business requirements for data quality, identifying key data quality dimensions, and developing the necessary business rules to ensure high data quality (Cia & Zhu 2015). According to Antonenko (2015:55), such a conceptual framework may be represented diagrammatically to show the inter-relationship between components to propose a solution to the research question. Linked to key components identified in developing a conceptual framework as per the underpinnings of the hourglass and DAMA models, the figure below provides context within which data quality can be managed in the banking industry through the use of AI.

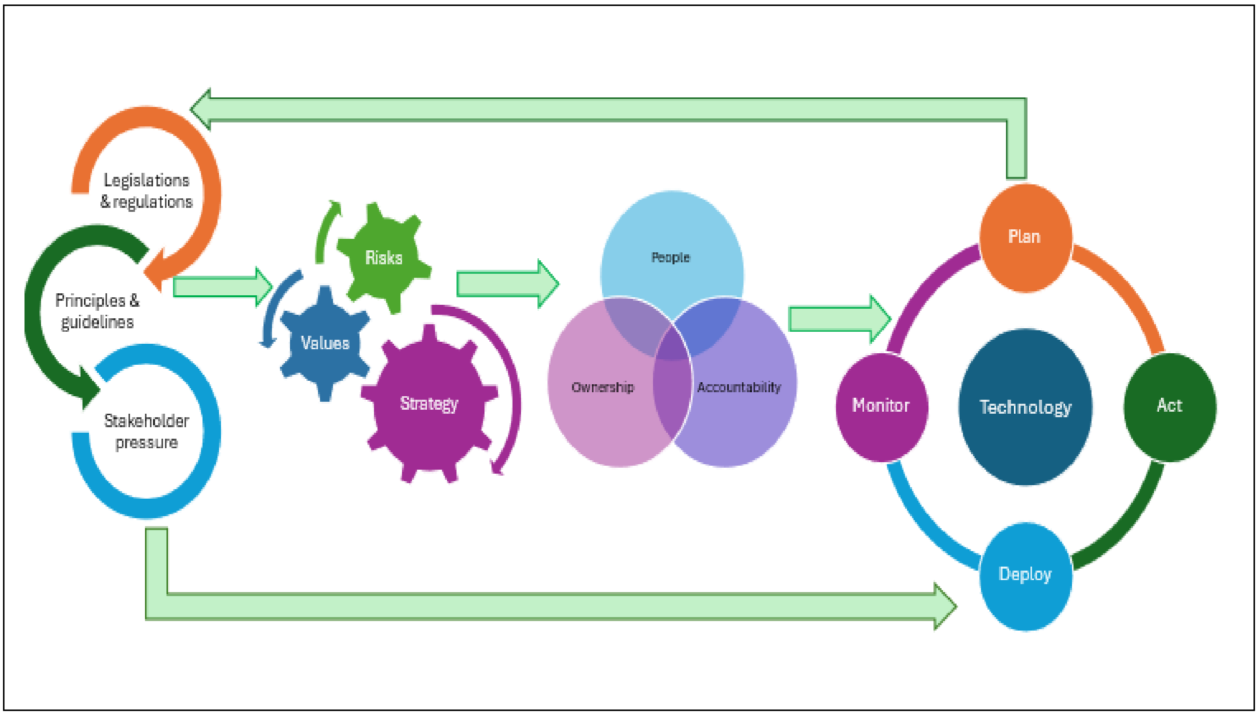

Figure 1: Conceptual Framework towards the use of AI in data management

It is important to note that financial institutions may face a plethora of data quality management considerations when adopting AI to assist in the execution of this task (Asamba 2019). This is due to data quality management practices being driven by legislation, regulatory requirements, and the possible introduction of new regulatory requirements for reporting, such as the BCBS 239 principles for risk data aggregation and risk reporting, as well as International Financial Reporting (Orgeldinger 2018).

Legislation and regulations inform the planning, actions, monitoring, and deployment of AI towards enhanced data management, while people, ownership and accountability in turn influence the systems and technologies used to implement AI towards improved data management. In the banking sector, the risks, values, and strategies used towards the implementation of principles, guidelines and stakeholder involvement further influence the application, as well as consideration of AI towards improved data management.

Laws and regulations in place within AI technology and data quality management are of importance when establishing an information governance framework to govern the use of AI technology for data quality management in the banking sector, as there are other risks at hand that need to be catered for by various laws and regulations. All businesses are impacted by laws and regulations, and data activities are no exception. An important part of data governance is to monitor these laws and regulations, and to make sure that they comply with them (DAMA 2008). Access to and use of any classified data, such as personally identifiable data, need to be regulated (Berson & Dubov 2007). For example, in the South African context, the banking sector needs to adhere to the POPIA. Another example of these regulations would be the GDPR, which concerns the previously mentioned personally identifiable data (Wolford 2020). Furthermore, regulations such as those of the BCBS's standard number 239 need to be evaluated, to see how they would impact on the use of AI technology for data quality management.

Through AI scholarship and practice, a plethora of self-regulatory documents outlining AI principles and guidelines have been established, with which researchers have produced overviews of the AI guidelines that have been developed (Hagendorff 2020:100). A review by Jobin, Lenca and Vayena (2019:389) outlines the convergence of principles around transparency, justice and fairness, non-maleficence, responsibility, and privacy as key elements. However, organisations need to develop their own governance models to avoid any contradictions that may exist within different principles (Morley et al. 2020; Georgieva et al. 2022). Also, data quality management processes that are governed by data governance principles and guidelines need to be established to support data security and privacy (Ladley 2019). Convergence of data quality management principles and AI needs to be developed as part of the information governance framework for using AI technology for data quality management in the banking sector. It is also important to note that for the successful implementation of these principles and guidelines, people need to participate and take certain actions (Sarsfield 2009).

People play a vital role in the implementation of laws, regulations, policies, and guidelines, as they are the driving force to ensure implementation. As mentioned before, stakeholder pressure on governing AI is still an understudied phenomenon and there are very limited studies on the awareness of AI governance issues among key stakeholders in organisations (Minkkinen et al. 2022). Data governance practices practically outline the accountabilities, decision rights, responsibilities, and rules that stakeholders need to adhere to (Ladley 2019). Outlining these roles allows for accountability of governance structures and shows ownership of the data that the banking sector needs to manage, which is important for ensuring that data quality management processes are not compromised, and activities are carried out correctly (Alhassan, Sammon & Daly 2019). The people who are assigned certain responsibilities are therefore accountable/responsible to ensure that AI and data quality management practices are embedded within the organisation, and they are responsible for prioritising these activities (Plotkin 2020).

Change management practices also need to be implemented for adopting an information governance framework within the organisation, and people need to adjust their behaviour according to the strategy developed (Ladley 2019). This can prove to be difficult, as people are often set in their ways of doing things and may not necessarily be ready for change (Bhansali 2014). Nevertheless, to successfully implement an information governance framework, organisations must adopt a three-step change management strategy of planning, doing, and sustaining (Ladley 2019). This makes it very important to have open communication channels with stakeholders and to involve them, as they are a necessary part of the entire process (Bhansali 2014). Proper communication leads to a good data culture and with high-quality data (Eryurek et al. 2021; Sulanen 2021). This leads to the next section that focuses on the importance of adopting the right strategy and technology for data quality management activities.

It is important that the organisational strategy aligns with the AI and data governance strategy, to allow for the smooth implementation or integration of these within the organisation. This allows the banking sector to define what AI systems the banking industry intends to use for data quality management and to outline the business goals that they aim to achieve with this strategy. It is important to establish a strategy in line with the organisation’s strategic goals (Brous, Janssen & Vilminko-Heikkinen 2016:102), to outline the long-term objectives and how these align to the company’s long-term business goals. The goals the banking sector aims to achieve within this study should be aligned with strategic objectives for managing financial data, and this is linked to improved decision-making with reliable data of good quality (Sulanen 2021). The goals should also align with the company’s strategic goals, to ensure that the data quality management plan supports the overall business strategy. Organisations always have values that inform their existence, and alignment between organisational values and AI and data management values is needed, since stakeholders need to live by these values. Identified values need to be incorporated into the system/technology part of the framework, as people and systems should be informed by such values.

Technology adopted for AI should encompass elements from the relevant laws, regulations, principles and guidelines, stakeholder pressure, strategy, risks, values, and input from the people involved (Alhassan et al. 2019:104-108). This layer is complex, because all the elements discussed in the above sections play a critical role in what goes into the technology/system used for data quality management with the use of AI technology. The AI technology utilised for data quality management in the banking sector in South Africa should be aligned to the organisational strategy, business strategy, data strategy and the AI strategy the organisation has in place. This will also ensure that the organisational values are adopted and addressed in the development of a solution to improve data quality management practices. It is imported to ensure that the AI technology adopted is operated and monitored and that its risks and impact are measured against the strategic goals of the organisation and the data governance strategic goals being catered for in the solution, to provide an information governance framework that will ensure that this process runs smoothly.

7 Conclusions

The aim of this research was to provide a conceptual framework for the use of AI to enhance data quality management within the banking sector. Five themes have been identified to ensure that data quality management practices can be improved with the use of AI technology within the banking sector. Improved data quality management practices within the banking sector will impact on the data analytics that influence improved decision-making within banks.

The proposed conceptual framework provides a starting point for the establishment of a data quality management framework for using AI in the South African banking sector. It is envisioned that the conceptual framework could be used for further research, linking data quality management practices and AI technology. The value of the paper is embedded in exploring the proposed conceptual framework and the application thereof, to determine the practical application of utilising AI in promoting data quality management in the banking sector. Further research is necessary to validate the conceptual framework, as well as the application of the conceptual framework within the banking industry to assess and substantiate the proposed variables.

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