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Intelligent Data Quality Framework Powered by AI for Reliable, Informed Business Decisions

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Abstract

This research looks into developing a data quality framework relying on AI to ensure more accurate decisions for financial companies, supply chain management, and healthcare providers. When data accumulates and comprehensive validation isn't achievable, organizations struggle with inconsistencies, redundant records, and missing information. Using natural language processing, anomaly detection, and machine learning, the proposed framework automatically cleans data, improves accuracy, and maintains consistency in various data systems. This research looks at workflows of AI and frameworks that are being put together to propose practical and scalable methods for better data use, and compliance within various industries.

Keywords: Artificial Intelligence (AI), financial services, supply chain management, healthcare, data systems, data accuracy, organizations, data governance

INTRODUCTION

In the current scenario, making strategic decisions in any industry strongly depends on data. On the other hand, the data an organization uses is low-quality, this often results in weak strategies, losses of money, and system inefficiency. There is now a greater demand for strong data quality frameworks because more organizations are using data to make decisions. This paper suggests using an AI-supported framework for data quality to support lasting, accurate, and wise decisions. This framework makes use of natural language processing and anomaly detection based on artificial intelligence to tackle essential problems linked to partial, non-uniform, and not always correct data. In this context, using an effective approach increases the precision and relevance of reports and cuts down the effort and the amount of time spent validating data manually. It is especially useful for data found in financial services, healthcare, and supply chain management, as these areas depend on quick and correct decisions.

Aim

The main focus of this research is to check an AI-assisted model for data quality that allows organizations to make solid business decisions in all data systems.

Objectives

- To explore the potential of AI in enhancing sound business decision-making by enhancing data reliability and accuracy in quality.
- To examine the data not only in rest but also in move, as part of data ingestion process. AI-based approaches to strengthen ‘data quality’ procedures within active and wide-ranging data systems
- To evaluate the workflow of ‘Artificial Intelligence (AI)' increases 'data accuracy', 'consistency', and integrity within complicated industrial sectors.
- To suggest an effective ‘AI-enabled framework’ for customized support to get more accurate decisions within ‘supply chain management’, ‘financial services’, and ‘healthcare sectors’

Research Questions

- “How AI can support informed business decision-making through improving the reliability and accuracy of data quality?”
- How to evaluate the workflow of ‘Artificial Intelligence (AI)’ increases ‘data accuracy’, ‘consistency’, and integrality within complicated industrial sectors?
- How to examine AI-based approaches to strengthen ‘data quality’ procedures within active and wide-ranging data systems?
- “How can AI enhance data quality to support informed and strategic business decision-making?

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RESEARCH RATIONALE

Supply chain management and healthcare are growing more complex data, there are now major difficulties in ensuring consistent data quality because of the complex data in financial services. The fast increase in data creates problems for getting accurate, complete, and reliable information in real-time. Mistakes and inconsistencies with data in these sectors make it hard to rely on data and undermine planning efforts. The efficiency of business operations is reduced because current data volumes and speeds cannot be verified manually. AI raises the possibility of new approaches to managing and fixing data issues, and there is more complexity when trying to add AI to current data systems [1]. In this context, AI tools have to address situations unique to each organization and relevant domain data to remain accurate and consistent. AI model will play a critical role in managing different types of data which is crucial for the quality of decisions in these industries.

LITERATURE REVIEW

"The potential of AI in enhancing sound business decision-making by enhancing data reliability"

Artificial Intelligence (AI) has become a revolutionary instrument in the quest to increase the robustness and validity of data, which enhances the premise of making good business decisions. Moreover, the absence of cohesive governance systems inhibits the usage of structural metadata and documentation to create efficient data quality regulations [2]. In modern information-driven economy, data quality has a direct impact on strategic performance, operational performance, and competitive advantage. machine learning, natural language processing, and anomaly detection are all AI technologies that can automatically identify and correct errors in data, integrate data across diverse sources, and constantly watch over data flows to identify inconsistencies. This is an adaptive and automated method that minimizes the reliance on the manual data cleaning process that is prone to error, time-consuming, and inconsistent.

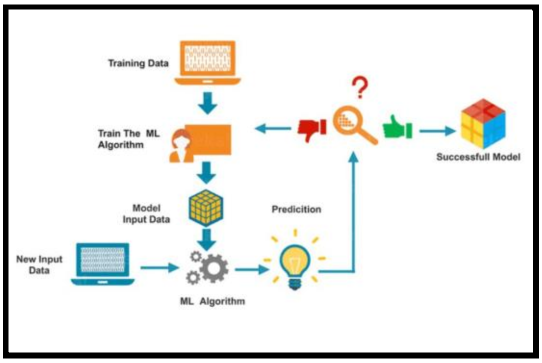

Fig. 1: Data Quality checking using AI

AI will help business leaders make decisions based on reliable and usable information because it enhances the quality of the datasets in terms of accuracy, completeness, and timeliness. AI-powered data quality tools are used in mission-critical areas like financial services, supply chain management, and healthcare to meet real-time analytics and predictive modelling needs as well as regulatory compliance. With such capabilities, organizations can identify risks before they occur, manage resources optimally and react quickly to any changes in the market.

Further, AI can boost data transparency and data governance through metadata management, lineage tracing, and explainable decisioning structures [3]. This confides the stakeholders in the automated decision-making processes. Comprehensively, in addition to improving the technical merit of business intelligence systems, AI infusion into data quality management would help make more informed decisions, more strategic and responsive business decisions in progressively more complex business environments.

"The workflow of 'Artificial Intelligence (AI)' to increase data accuracy, consistency"

Organizations in finance, supply chain, and healthcare are creating vast quantities of complex information, and the traditional tactics for managing data quality are limited. In this context, these sectors count on accurate, unchanging, and prompt data to make important decisions, avoid breaking rules, and work efficiently. 'Data redundancy', 'inconsistency', 'incompleteness', and human errors are seen on account of using disconnected data systems and manual techniques [4]. There is an increasing call for smarter, larger, and more adjustable approaches that boost data accuracy and consistency. The process of improving data quality is much easier, as it can learn from what it observes, detect errors, and automate important steps with AI. AI technologies allow data workflows to automatically check for problems in incoming streams, report them on the spot, and adjust any differences found in various sources. With the help of this capability, 'financial services can detect fraud more easily, ‘supply chain’ managers can keep inventories synchronized, and healthcare providers can increase the accuracy of patient records [5]. Additionally, standards set for data governance in each sector should be used to ensure credibility and visibility. This research aims to explore the complete workflow of AI so that data is more 'accurate' and ‘consistent’ in leading industries.

“AI-based approaches to strengthen ‘data quality’ procedures in wide-ranging data systems”

Businesses in the financial services, supply chain, and healthcare areas rely heavily on the quality of their data to help them make smart and prompt choices. Wide-scale data systems usually struggle with problems such as data variance, gaps, multiple entries, and errors, which can markedly reduce the working structure of a company and what it achieves. In this context, using traditional methods to check data quality and using static rules is not enough for the rapidly increasing amounts of data facing these industries [6]. For this reason, more businesses now use AI to provide flexible, automatic, and scalable systems for improving their data quality.

Fig. 2: Best Practices for Data quality management

Tools like machine learning, anomaly detection, and natural language processing allow organizations to constantly monitor their data systems, quickly find errors, clean the data seamlessly, and watch for trends. AI in financial services helps detect fraud and smoothly adds regulatory information because it allows for accurate data; AI in the supply chain aids in coordinating inventory and logistics [7]. AI in healthcare protects patient information by making it stable and accessible anywhere. There are obstacles involved in combining AI and old datasets, mainly due to issues with data control, ethical rules, and the interaction of existing parts of the system. The research is conducted to explore the effectiveness of AI can effectively resolve data quality problems in different and complicated data systems.

“The enhancement process of AI to data quality to support informed and strategic business decision-making”

Artificial Intelligence (AI) has become a revolutionary technology in the area of improving the quality of data, and hence empowering businesses to make informed and strategic decisions, irrespective of the sector. The most fundamental aspect of such enhancement process is that AI will automate the process of identifying, correcting, and validating data anomalies [8]. Conventional data quality processes usually have a hard time keeping up with the complexity, volume, and speed of contemporary datasets. AI technologies, including machine learning, natural language processing (NLP), and anomaly detection algorithms, in turn, can analyze both high amounts of structured and unstructured data making the results reliable [9].

Real-time data clean-up is supported to identify duplicates, outliers, missing values, or semantic inconsistencies using AI. These facilities guarantee that business analytics and predictive models get developed using precise datasets, which is vital to make productive decisions. Further, AI can improve data integration, harmonizing heterogeneous data sources into common frameworks, to enable a single source of truth in strategic analysis [10]. This increases the accuracy of forecasting, risk analysis and optimization of operations in fields such as finance, healthcare and supply chain management.

Also, AI brings a concept of adaptive learning wherein models can change with respect to new patterns in the data, continuously improving the accuracy of the data with time. This is an iterative learning, which brings about ongoing data governance and compliance enhancement. Businesses may also interpret the data outputs through explainable AI techniques embedded, which allow transparency in decision logic. **Literature Gap**

AI is mainly being used in data quality research to detect odd patterns or set up automated processes. The research does not bring together these separate components to form a single adjustable AI framework for the sector. Small practical work has been done to apply AI to older or different types of data systems.

METHODOLOGY

This report follows “***Secondary data sources***” because detailed information from publications, studies, and reports exists about the AI-based ‘data quality framework’ for accurate and informed decisions. The existing report examines this method to check an AI-assisted model for data quality that allows organizations to make solid business decisions in all data systems [11]. Secondary data is a useful data source in this report to investigate the potential of AI in enhancing sound business decision-making by enhancing data reliability, with a detailed analysis of innovative data systems. The researcher selected "***interpretivism philosophy***" because it aims to evaluate the workflow of 'Artificial Intelligence (AI)' and increases 'data accuracy', 'consistency', and integrity within complicated industrial sectors [12]. The interpretive philosophy investigates AI-based approaches to strengthen 'data quality' procedures within active and wide-ranging data systems.

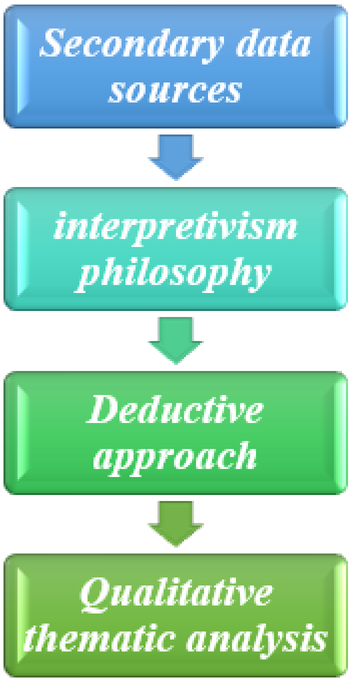

Fig. 3: Methodology

The selected approach has singular significance in combining AI and old datasets, mainly due to issues with data control, ethical rules, and the interaction of existing parts of the system. This report applies a ***deductive approach*** to evaluate the effective 'AI-enabled framework' for customized support to get more accurate decisions within 'supply chain management', 'financial services', and 'healthcare sectors'. The collected information in this report goes through "***Qualitative thematic analysis***," which enables researchers to determine and analyze the workflow of 'Artificial Intelligence (AI)' increases 'data accuracy', 'consistency', and integrity [13]. The thematic analysis utilizes this method because it offers a comprehensive analysis of the AI-based framework is successful in data governance, sticks to ethical rules, promotes 'interoperability', and ensures good system integration. Data patterns in the gathered information qualify researchers to demonstrate significant findings about best practices and challenges, along with an AI-based Data Quality Framework.

DATA ANALYSIS

"Theme 1: Challenges of Using AI in Evaluating Data Quality and Mitigation Strategies"

Artificial Intelligence (AI) is a game changer in the automation of data quality assessment areas, though there are a number of issues that remain a barrier to its optimum performance. The problem of algorithmic opacity, also known as the "black box" problem, in which the inner logic of AI models is hard to interpret, particularly to non-technical stakeholders [14]. Such lack of explain ability might result in a low level of trust in AI-based quality estimation especially in strictly regulated industries like healthcare and finance. Moreover, AI models have a fundamental weakness that relies on training data quality. Incomplete or unrepresentative, the models may give inaccurate or biased output, thereby reinforcing the original problem in the data quality When the input data is biased.

'Model drift' is another major issue category, where AI models lose their quality over time because of the shifts in data patterns or business processes [15]. This may cause inconsistency in quality assurance unless the models are constantly tracked and re-educated. In addition, the technical and functional challenges of incorporating AI tools into legacy systems include compatibility problems and organizational inertia to changes.

In order to avert these vulnerabilities, a number of mitigation measures are proposed. The adoption of explainable AI (XAI) methods enables having a deeper understanding of the decision-making process, thereby instilling stakeholder trust [16]. It is also important to put in place governance structures that will help in providing ethical use, fairness and accountability. Instead, organizations must use dynamic model validation and feedback loop in order to adapt to changes in the data. Finally, and no less importantly, the integration of domain experts into the process of AI development allows keeping models contextually relevant and in line with real-world expectations. All these measures combine to increase the trustworthiness and integrity of AI-driven data quality assessments.

"Theme 2: The workflow of 'Artificial Intelligence (AI)' increases 'data accuracy', 'consistency' within complicated industrial sectors"

Artificial Intelligence (AI) is transformative in the way it helps to automate and improve the data quality processes across the industrial sectors that are complex in their nature and require Artificial Intelligence to clean up the data and make it accurate and consistent. Among the main benefits is the fact that AI can enhance the consistency of the data, identify duplication, and inconsistency without using deterministic field-based joins. 'Data matching' is made more flexible and accurate through natural language processing and generative AI [17]. Also, AI aids in adaptive data quality management which dynamically adjusts thresholds based on sophisticated machine learning models that allow a more responsive approach to changing data conditions. The semantic level of understanding is possible through the integration of large language models (LLMs), providing the capabilities of higher-order lineage-based, cataloging-based, and glossary-based validation.

In financial services, AI finds and prevents fraudulent cases; in supply chains, it helps keep inventory levels current and guess future demand [18]. In healthcare, it improves keeping records accurate and helps transfer patient information safely. These AI-supported methods help companies perform data operations with consistency and can easily handle increased volume with no drop in quality. Additionally, AI helps systems transform with changes in data and requirements of a business. Moreover, AI enables guided root cause analysis by trace new anomalies back in time to prior incidents via data lineage, sparing a great deal of manual debugging work [19]. These capabilities also promote anomaly detection, semantic validation, and rule suggestion at scale towards intelligent, scalable data governance.

"Theme 3: AI-based approaches to strengthen 'data quality' procedures within wide-ranging data systems"

Organizations in financial services, supply chain management, and healthcare rely heavily on data for their most important work, and the need to increase data quality in many systems is more urgent. These sectors often store many various, overlapping, and faulty data, which results in less accurate data, slower operation, and missed compliance standards [20]. Using traditional methods, data quality procedures have trouble handling these challenges on a broad scale. In this context, the data, artificial intelligence provides methods that can revolutionize the way data quality is managed. Artificial intelligence makes it possible to automatically check, clean, and check for any changes in large bodies of data. AI is used in the financial sector to streamline transaction reconciliation and bring together risk data. In supply chains, it makes it possible to monitor inventory against suppliers' information, and in healthcare, to ensure health records are accurate and have fewer errors [21]. The organizations run on their own, noticing trends, catching mistakes, and becoming better at their work whenever new types of data arrive. AI further helps by bringing together different data sources using one set of standards, that makes organizational data more trustworthy and easier to use. It is important to look at 'data governance', understand the algorithms, and stick to ethical standards to make sure everyone trusts and is responsible for AI [22]. It shows that using AI-based techniques strengthens the quality of data and makes it simpler for organizations to handle, structure, and decide on their data resources.

"Theme 4: Enhancing Data Quality through AI-Powered Semantic Intelligence and Adaptive Learning"

Artificial Intelligence, namely generative AI and large language models (LLMs) is transforming the territory of data quality management, offering semantic intelligence, adaptive rule generation, and guided diagnostics [23]. More complex inconsistencies, duplications or semantic errors may be difficult to detect using traditional approaches based on deterministic joins and hard-coded data validation logic. AI fills this gap by making the matching of the data more flexible and intelligent even without the hardcoded mappings based on the natural language processing and understanding the context.

Machine learning models have the ability to dynamically adjust the data quality thresholds enabling organizations to create more responsive and changing quality standards [24]. LLMs also allows moving beyond shallow field value checks and instead uses metadata like lineage, glossary definitions, and cataloging to determine data quality on a more semantic level. Such holistic insight promotes semantic data interpretation and more validation richness.

AI can also augment root cause analysis by relating the existing anomalies with past problems and following the data lineage. This saves tremendously on manual debugging time and reveals unfamiliar patterns on data failures [25]. Furthermore, generative AI interfaces enabled by chatbots, when trained on typical data problems and quality rules, can provide proactive detection of anomalies, propose validation logic and generate quality rules enabling organizations to gain greater accuracy, consistency and confidence in their data assets.

FUTURE DIRECTIONS

The major focus in research is needed to fashion adaptable AI-driven frameworks that can self-adjust and cope with big data challenges found in financial services, supply chain management, and healthcare. The frameworks will add advanced deep learning features to boost anomaly detection, on-the-spot corrections, and data prediction accuracy. In this context, future designs will connect well with existing systems and closely focus on ensuring that AI is used ethically and openly [26]. Additionally, case studies that involve many sectors will be done to prove the framework of useful AI frameworks in real-life applications. The aim is to implement standard rules for connecting AI with company data systems, so that both rules and data are standardized everywhere.

CONCLUSION

Better data quality can be achieved for the financial services, supply chain management, and healthcare industries using an AI framework. According to the study, earlier data quality standards fail to handle and fix the range of data issues in modern data systems. Operational progress is slowed by the complications of data redundancy, inconsistency, and outdated records. It is clear from looking at AI workflows, approaches, and frameworks that AI makes it possible to scale, automate, and improve the accuracy, consistency, and integrity of data. The use of AI means that systems can monitor themselves all the time, clean up automatically, recognize unusual events instantly, and help with decisions relevant to each industry sector. Ultimately, AI is fundamental to changing and improving data systems used in today's supply chain management.

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