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Review Article

Comparative Analysis of Traditional and AI-Driven Data Governance: A Systematic Review and Future Directions in IT

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Abstract *- In this context, this paper aims to offer a systematic review of data governance with a specific focus on the traditional approach to data management and the AI-based approach. The second paper reviews advancements in data governance frameworks, concurring with the importance of stringent control where data volume and variability are rising. The literature review also discusses core concepts tied to conventional governance frameworks, focusing on how AI revolutionizes data handling. By comparing the cases, the study points to how AI offers fresh opportunities regarding data governance responsibilities, productivity, and issues such as real-time data management. Finally, the review brings out the key conclusions on the subject matter, culminating in exploring how AI integrates reliability, conformity, and the lifelong management of data for organizations.*

Keywords *- Data protection and AI, Data governance, Artificial Intelligence in data governance, Traditional data governance, AI systems, and Data Governance.*

1. Introduction

Data governance has evolved as an essential area of interest for organizations aiming to achieve the highest possible business value from their data resources while avoiding misuse, data fraud, and failure to conform to set industry legal requirements. [1] In recent years, there has been a dramatic increase in data volumes due to the progress of information technologies, big data, and artificial intelligence. [2] As a result, organizations face an enhanced obligation to implement adequate systems supporting the correct management of data during the whole data management process. In its simplest terms, data management is synonymous with control and authority. In the past, data governance was handled through paper records and hardcopy documents supported by strict internal/external regulations, and human intervention in managing the challenges inherent in big data. [3] Nevertheless, the existing use of adaptive intelligence and machine learning is changing various companies' and organisations' overall data governance landscapes. AI-driven data management applies automation mechanisms and analyses of big datasets, which have become crucial for modern organizations. Not only does this transition enhance productivity, but it also yields new questions about trust, openness, and responsibility in the automated decision-making processes. Thus, this scholarly article discusses the development of the data governance process, including the use of AI and classical methods. The study also seeks to sample the state of practice with a focus on the emerging Application of Artificial Intelligence as the complexity of data management continues to rise in the modern era due to increased automation of data processes. Thus, this paper aims to provide a systematic literature review to present a broad view of the state of the art, the challenges, and future developments of data governance. It will also discuss the references made to compare the traditional data governance model with the implementation of the AI-based data governance framework and the working performance of both to ensure that the emerging needs of an organization are being fulfilled.

Key research questions that will guide this paper include:

- Where has the practice of data governance come from, and what components form the basis of traditional data governance?
- What specific benefits has AI brought to improving data governance, where data quality, trust, and regulation are concerned?

- What are the differences between the classical approach and AI in data management?
- To what extent are the current and future data governance trends comparable in the context of growing development in technology and data?

Since this paper will use a systematic review approach, acceptable articles and publications will be chosen systematically depending on pre-determined inclusion and exclusion criteria. Various aspects of data governance are highlighted in the selected articles, which highlight different conceptual perspectives, empirical evidence, and explanations of the dynamics of shifts in data governance practices across organizations. Considering the emergent findings of these schemes, this paper will aim to develop a comprehensive understanding of the changing nature of data governance and a set of future research propositions and implications for practice. In the subsequent chapters of this article, the literature review will discuss the practical application of traditional and AI-based data governance, the differences between the two approaches, and the prospects of data governance in the IT field.

2. Literature Review

In the last few years, data governance has emerged as a critical concept since more and more organizations operate in the context of growing data intensity. Increased awareness of data as an important organizational resource has led to increased efforts to create frameworks that can be used to manage, protect, and ethically utilize data. [4] Here, we investigate the history of data governance through traditional data governance models, current and new frameworks, the import of AI integration, and the challenges and opportunities of data governance in contemporary environments.

2.1. Evolution of Data Governance

Data governance can be defined as a concept that developed from information management. [5] Data governance initially grew as a concept, and the implementation of early frameworks was piecemeal and usually centered on data quality, security, and compliance. Schneider et al., in one of the earliest papers on this topic, state that there is no overall perspective on data governance. [4] As pointed out by the authors, data governance maintained its burgeoning prominence but did not attract standard formulization attention. Through a structured literature review of 145 research papers, the authors developed a conceptual framework that decomposed data governance into six dimensions: duties and responsibilities, working procedures, regulation, norms, actualization, quality, and control. This framework can be used to explain how organizations manage data systematically. Earlier data governance concepts tended to center more on data quality, data quality control, and data access. [4] Traditional models prioritise networked individual human decisions and the active use of override mechanisms to control data management processes. Chief Data Officers (CDOs) and data stewards were also identified as parts of these models and chartered to enforce discipline and standardization of data. [3] Other forms of knowledge were available for structuring data governance frameworks that encompass the knowledge of managing data, as provided in the Data Management Body of Knowledge (DMBOK). However, as the volume and range of the data were being generated and collected, the models started demonstrating scalability and flexibility issues. [5]

2.2. Traditional Data Governance

A traditional data governance model can be described as a bureaucratic approach grounded in top-down, authoritative structures defined by rigid rules and operations usually managed through paper-based methods. More emphasis has been placed on procedures and guidelines that would help translate data into a well-coordinated entity that is very much in tune with regulatory compliance requirements. [2] This proved useful during the period when information was limited and could easily be contained. However, with the introduction of real-time data management in organizations, weak points of traditional governance proved vital. The levels of traditional data governance that Paul and Janssen discussed in their article aim to promote trust in data science decision outcomes. [6] The authors consider two cases in the asset management domain and found that data governance is critical to enhancing the uptake of data science outputs by decision-makers. Some scholars claim that conventional governance architectures assist in developing trust by maintaining data credibility and controlling circumstances within an organization. [3]

However, the study also addresses that problem-solving in data science endeavors requires more flexible organizational structures and processes as the tasks become increasingly complex. [6] Using static mechanisms and control from traditional governance may hamper decision-making flexibility and force a slow reaction to dynamic environments in data. The strengths of traditional data governance include compliance, accountability, and identification and definition of roles and responsibilities. [7] Nevertheless, it has limitations in performing sufficiently to meet the needs of high velocity and voluminous data with high variety, as is typical in data ecosystem algorithms. [8] Most contested AI and machine learning solutions are used to process large amounts of data in organizations, and their governance can no longer be addressed under traditional governance structures.

2.3. AI-Driven Data Governance

The use of AI in the process of data governance means a new approach to data management and control. AI-driven data governance brings in automation and real-time analysis capabilities in data usage so that organizations can handle large amounts of data with higher efficiency and effectiveness to respond to the changes in the data environment. , as argued by J. Marijn, Brous, Estevez, Barbosa, and Janowski, the emergence of BDAS brought improvements in the data governance capacities, which are more fit for dealing with the embeddedness of Artificial Intelligence algorithms in decision-making. [5] Their study focuses on the trustworthiness of AI systems in making high-stakes decisions on behalf of the people and society. This is because there is a need for sound governance structures relating to transparency, accountability, and ethical supervision. [9]

AI-enabled data governance frameworks are distinct from conventional frameworks in several ways. First, they mostly use automation to implement and enforce compliance with the governance policies and standards. This cuts out the need for complex and time-consuming interventions that would otherwise be required for governance at higher volumes of data. [5] Second, AI systems can improve data quality by learning and detecting mistakes when entering or updating data in effective real-time, thereby increasing data correctness. Third, AI-driven governance frameworks are more prepared than rule-based frameworks to deal with the changing nature of contemporary data environments, where data comes in a stream and frequently changes. Atul views that an automated intelligent data governance system will help address the increasing volume of data. In his work, he presents BodhiCurate – an AI, Big Data solution that would perform data governance tasks autonomously with little supervision. [10] The system relies on AI characteristics to handle structured datasets so as not to overburden data stewards and administrators. Thus, the use of AI can enhance the effectiveness of the governance work of an organization at the same time maintaining data compliance with the requirements set by legal regulators and ethical standards. [2]

However, there are a set of issues that are also associated with the use of artificial intelligence in data governance. Introducing AI systems in organizations brings new risks, which include algorithmic bias and opacity of decision-making. [1] AI systems' fairness, accountability, and transparency should be suitable for integration into the data governance strategies, or subsequently, they should be adjusted to those guidelines that will sanction their deployment. In their article, Yanamala and Suryadevara, the authors rightly consider data protection as an inevitable prerequisite of AI-driven governance systems while discussing the role of GDPR. [9]

2.4. Challenges and Opportunities in Data Governance

The transformation of data governing from the conventional approaches to the AI-based has its risks and opportunities. [5] One of the biggest issues is the question of how AI will be transparent and how it will effectively explain why it arrived at certain conclusions as it is being used in high-risk and high-stakes areas. AI decision-making often inherits concerns around fairness since the precise working of the algorithms is frequently not straightforward for the organization to understand. Thirdly, data generation is faster than before, and there are more diverse sources, which also opens new problems of governing data. That is why AI-driven governance is also an opportunity for organizations and presents many benefits. By taking over routine governance tasks, AI systems can alleviate the extent to which true human data stewards are overloaded and can better handle more data. [10] AI can also add credibility to data, plus it is personal to the data science and decision-making process.

From the literature review, it is evident that data governance is an emerging concept that is progressively evolving as organizations transition from conventional and fully manual data management practices to automated and even artificial intelligence-based ones. Although conventional data management programs form a strong foundation for building, these are now augmented or even replaced by AI-anchored models that afford enhanced functionality, flexibility, and extensibility. [5, 10] Nonetheless, integrating AI in data governance can be successful while addressing ethical/regulatory challenges and the principle of explanation. It is expected that as organizations experience new challenges in managing and utilising data, the future of data governance will be influenced by the new developments between conventional models and AI technology advancements. [12]

3. Materials and Methods

This chapter presents the method used to systematically review the data governance literature, including traditional and AI-based methods. Consequently, the study seeks to accomplish the following objectives: Compare the two data governance models and identify the emerging concepts of data governance, especially within the IT domain. The study was carried out based on data collection, demarcation of articles selection criterion, articles inclusion and exclusion, and data analysis.

3.1. Research Design

For this study, a systematic literature review was used as the main type of research. In this case, the present approach guarantees an inclusive and credible assessment of the literature on data governance. The papers' systematic review process and analysis were done according to the flow chart developed to conform to the Reporting Question: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). As illustrated in the Table 1. The PRISMA table offers a sound approach toward the inclusion of potential works for review and the criteria for assessing the quality of the included research papers. This present research aims to synthesize literature that captures conventional and AI-integrated communication and data governance approaches, insights into their effectiveness and limitations, and potential development of the communication and data governance discipline amid accelerating technology disruption. The review also explored how these models have impacted organizational performance, compliance, accuracy, and security.

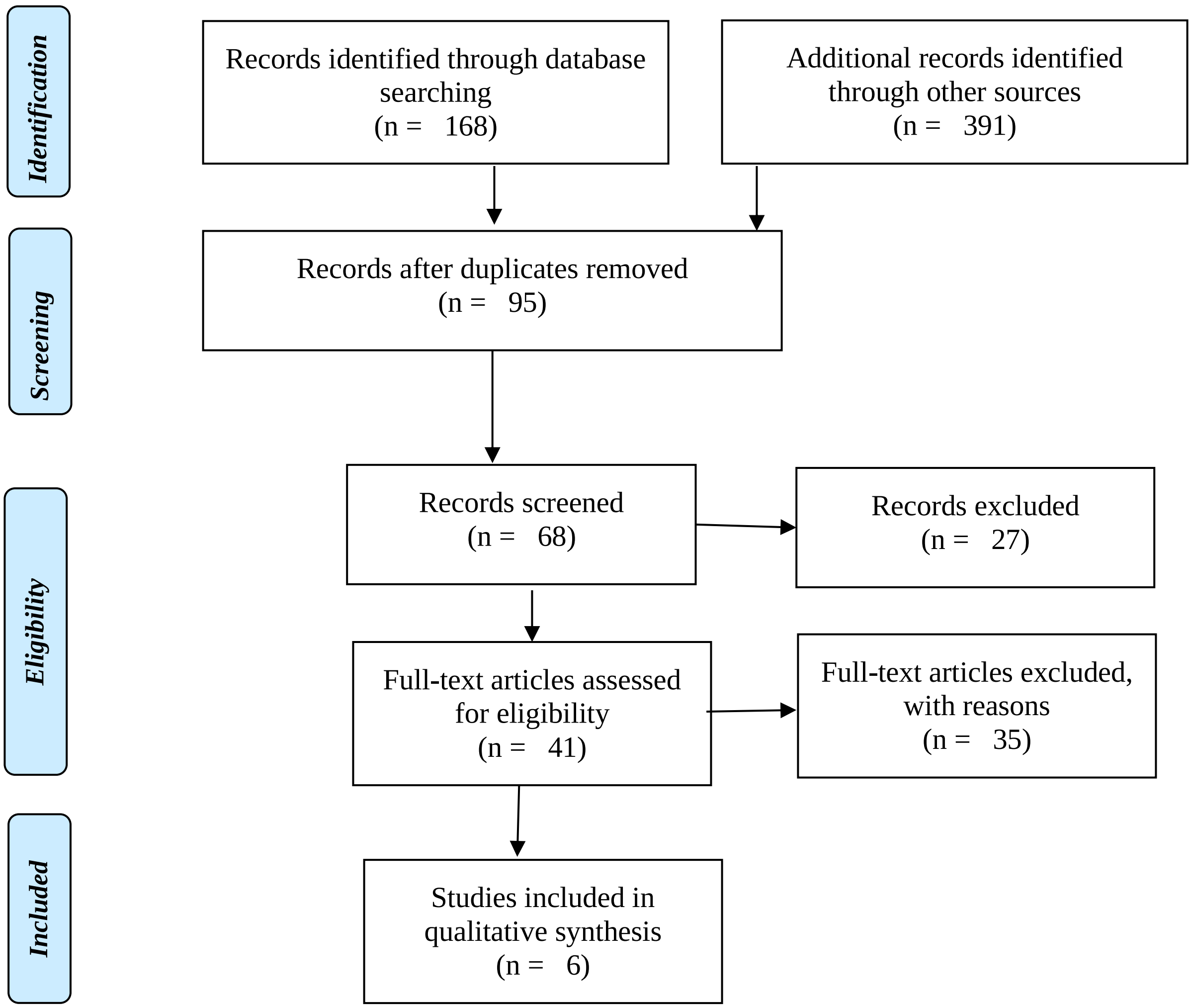

Fig. 1 PRISMA

3.2. Data Collection

This literature review involved Google Scholar, IEEE Xplore, JSTOR, and Scopus, from which data were gathered. These databases were selected as they contain many peer-reviewed articles, technical papers, and conference proceedings in data governance. To achieve that, keywords and phrases were used as a search string, including data governance, artificial intelligence in data governance, traditional data governance, AI-driven governance, data management frameworks, and the future of data governance. The current scientific literature review was cyclic, with different keywords and combinations to ensure all articles were identified. Electronic databases were searched for keywords, resulting in over two hundred articles, of which only those meeting the inclusion and exclusion criteria were used for analysis.

3.3. Inclusion and Exclusion Criteria

The inclusion criteria for selecting articles were as follows:

- Journal articles and conference papers that are peer-reviewed.
- Scholars of IT, AI, or fields related to technology data's efficacy in data governance.
- Articles were published between 2010 and 2024 to ensure that work included the most current advancements in the literature.
- The investigations compared the conventional and next-generation data management frameworks.
- Exclusion criteria included:
- Such articles failed to post a coherent approach towards data governance.
- Literature was published before 2019 unless they offered a literature review that served as a basis for the current research.
- The articles are more peripheral to its topic and may be from other areas of study, such as healthcare, education, or a business method.

The criteria used to exclude these articles are described under the exclusion criteria section above; after applying the criteria, 6 articles were selected for full review, as further illustrated in Figure 1 above. Table 1 below shows the list of included articles.

Table 1. List of included articles

Author and Year of Publication	Title of Research Article	Journal/Conference/Publisher
A. Rene, J. Schneider, and Jan Vom Brocke (2019)	"Data governance: A conceptual framework, structured review, and research agenda."	International journal of information management.
J. Marijn, P. Brous, E. Estevez, L. S. Barbosa, and T. Janowski (2020)	"Data governance: Organizing data for trustworthy Artificial Intelligence."	Government information quarterly.
B. Paul, and M. Janssen (2020)	"Trusted decision-making: Data governance for creating trust in data science decision outcomes."	Administrative Sciences.
L. Dominik, and B. Otto (2020)	"Data governance in data ecosystems–insights from organizations."	Data Governance in Data Ecosystems.
V. Salomé (2021)	"A relational theory of data governance."	Yale LJ.
A.K.Y. Yanamala, and S. Suryadevara. (2023)	"Advances in Data Protection and Artificial Intelligence: Trends and Challenges."	International Journal of Advanced Engineering Technologies and Innovations.
A. Atul. (2024)	"AI-driven data governance for the enterprise intelligence."	Indira Gandhi National Open University (IGNOU).

3.4. Data Analysis

In this study, the selected articles underwent a qualitative content analysis to be interpreted. Every paper was then read to identify common themes, study outcomes, and research approaches. The analysis was conducted to consider the trends of traditional and AI-based data governance, as well as the problems and prospects for developing the scope of data governance. The conclusions derived from these articles were compared into comparative frameworks that embraced these issues about automation, scalability, data quality, compliance, and organizational impact, which contrasted the two approaches.

The approach in this research made it possible for the author to conduct an exhaustive analysis of the literature about data governance. In this respect, this study adheres to a systematic way of collecting and interpreting the information that makes the basis for subsequent evaluation and comparison of the traditional and AI-based approaches to governance and the prognosis of future developments in the field.

4. Results and Discussion

This chapter brings the findings of the systematic review of literature on data governance in the traditional and AI-based methodology and the prediction of the future of data governance in IT. The results are then presented, along with the research questions, and a further general discussion about the implications of such findings is provided.

4.1. Summary of Findings of the Systematic Review

A comparison of traditional and AI-based approaches to data governance was conducted during the literature review to compare and contrast the two and come up with each model's relative merits and demerits. The review also revealed new and developing trends and issues organizations experience when implementing data governance frameworks.

4.1.1. Traditional Data Governance

Traditional data governance can thus be understood as business processes, rules, and structures that individuals attempt and manage to maintain superior data credibility, security, and adherence to laws. [8] These models require close manual supervision and clear divisions of labor, positioning figures such as data stewards, data custodians and governance committees at the heart of these approaches. What is more, within most traditional Governance frameworks, including the DAMA-DMBOK, there exist practices that guide the management of data as an asset. [11]

The review established that previous data governance solutions are applied in organizations where data is relatively fixed, organized, and exists in a single firm. Some of the main advantages of traditional governance are the best practices for controlling the quality of data, observance of the legislation, and difficulties in assigning responsibilities. However, traditional data governance becomes challenging in terms of the volume of data, the unstructured data, and the dynamic technology environment.

Table 2. Comparative analysis of Traditional Data Governance and AI-Driven Data Governance

Aspect	Traditional Data Governance	AI-Driven Data Governance
Scalability	Not easily scalable. Not suitable for large and unstructured data sets	High scalability, processing of real-time data
Adaptability	Some organizations face the challenge of adapting to sudden improvements in technology.	Very versatile, receptive to using new data feeds
Compliance Management	Adherence to legislation, audits conducted by human beings	Compliance is automated, and compliance monitoring in real-time
Data Quality	Manual processes ensure data quality	Automated inspection, device, and condition monitoring
Decision-Making	Dependent on human judgment	Utilizing data and analytical processes through Artificial Intelligence for decision making
Challenges	Lack of flexibility and high costs associated with performing the process manually	Challenges include the complexity of the models, the ability to explain the model's decisions in an easily understandable way, and legal and ethical issues.

4.1.2. AI-Driven Governance

Data governance using AI uses c Mogul AI, which applies machine learning, automated tools, and analytics to manage the data. With the help of AI, it becomes possible to process massive amounts of data in real-time, which becomes increasingly important as the amount and the variety of data are constantly increasing. [5] Using inherent governance models, data could be categorized, lineage could be tracked, anomalies could be noted, and unnecessary manual checkups could be eliminated. The review established that data governance through AI is most relevant in dynamic, heterogeneous conditions and requires real-time analyses, such as BDAS and IoT. AI-based governance systems present improved scalability, flexibility, and effectiveness compared to traditional systems, enabling organizations to adapt to modifications within the data environment.

Further, AI systems can detect things in the context of data that are beyond the means of traditional systems, enhancing the making of decisions and predictive intelligence. Nevertheless, issues arise with the implemented AI for governance. This is the case in the following areas: interaction with the current governance structures, transparency and interpretability of AI models, and treatment of ethics issues connected with AI decision-making prejudice and unbiasedness. [10] Also, there is a need for organizations to support robust data architecture as well as experienced professionals to work on and with AI.

4.1.3. Comparative Analysis

The literature review concluded that there were several differences which are highlighted between traditional and AI-driven data governance, as illustrated in Table 2. The findings show that the approach used in traditional data governance is efficient in inspected, consistent scenarios, but in the contemporary environment of increasing data demands, it is barely sufficient. In contrast, AI-substantiated governance offers robust solutions for regulating data intensity; however, ethical and technical considerations hinder its application.

4.2. Discussion

For this reason, the literature review highlights the collaborations between traditional data governance and AI approaches. In this context, rather than offering a new set of solutions that could fundamentally replace traditional approaches, the concept of AI-driven governance could complement them by offering solutions that can address issues of scalability, employability of tasks, and decision-making. [10]

4.2.1. Modern Organization and the Relevance of Traditional Data Governance

The concept of traditional data governance can still be applied in many organizations, especially in industries subject to the most stringent regulatory standards, including financial and healthcare ones. [11] A key benefit of the traditional governance structures is that responsibilities for data are always allocated and checked; usual best practices and protocols are followed. [12] Secondly, conventional governance is effective for handling high-risk information, where human control is essential for trust and compliance purposes. But, as the complexity of the data environment rises, organizations learn that traditional governance is insufficient for their needs. Due to these considerations, these systems lack scalability and flexibility and cannot meet the demands of real-time or unstructured Big Data. Therefore, traditional governance is required to become more autonomous and based on AI components that address such complexities.

4.2.2. The Advantages of AI-Driven Data Governance

Several qualitative differences exist between the AI-governed model and conventional types of governmental systems. First, its real-time capability of handling big data makes it a perfect candidate for handling dynamic data contexts encompassing IoT and machine learning. It also optimizes decision-making since AI brings the element of advancement by pointing out the existing patterns, derived trends, and abnormalities in the large stack of data. Moreover, substantive use of artificial intelligence in governance improves compliance management since it enforces checking and auditing practices concerning data usage, minimizes the occurrence of compliance breaches due to human mistakes, and guarantees that the organization remains lawfully suitable. This is especially true when data privacy standards are tightening across the globe, for instance, with GDPR.

4.2.3. Challenges and Considerations

AI-driven governance is not without its main problems. The high dependence on these models creates issues of interpretability and traceability, which are sensitive in industries with high accountability. [9] Those selecting or implementing AI solutions for governance must guarantee that the models can be explained and are not prejudiced; in other words, AI models for governance must be audited and validated. However, ethical considerations raise other issues when using artificial intelligence in data management. For instance, there are biases where inferences and decisions made by an AI model reflect unfair decisions made from biased data. Solving these problems necessitates organisations adopting and incorporating ethical standards and regulations for Artificial Intelligence operating on data. [5]

4.2.4. Ethical Implications of AI in Data Governance

AI addition in data governance poses multiple ethical questions. AI makes the provision of solutions better and quicker but has complications in biasness, openness, and responsibility. Designed algorithms have been found to favor or even exaggerate some forms of discrimination, especially wherever the data input set is not diverse enough. [5] Furthermore, one of the biggest criticisms of the use of AI – the so-called 'black box' problem – is that decision-making becomes virtually impenetrable by stakeholders who cannot effectively scrutinize and question determinations that have been made. There are also privacy issues since AI applications order large amounts of data that can otherwise be abused or hacked. In addition, outsourcing governance tasks to AI systems increases confusion about who is to blame; it is not always clear whether developers, organizations, or the AI itself is to blame. Such ethical issues call for sound structures of fair and easily understandable catalysts with regulatory compliance solutions. Addressing these challenges is important to ensure that the use of AI-driven data governance results in decision making that reflects societal values while simultaneously creating the much-needed trust in IT systems to drive innovation.

4.2.5. Criteria for Evaluating the Differences between Traditional and AI-driven Approaches

When comparing traditional and AI-based data governance, some important factors need to be considered: efficiency, accuracy, and transparency. Conventional techniques are usually based on a set of rules, which can be more labor-intensive, especially in rapidly changing data conditions. In contrast, AI-driven methods have better control over automation and scalability since a larger volume of data can be processed and analyzed, making decisions faster and in real-time. Precision also becomes important because inputs in traditional systems can be erroneously compared to AI, where its effectiveness and efficiency depend on its algorithms and data. Nonetheless, transparency is quite contrasting; conventional systems have outlined unambiguous procedural protocols and procedures, and AI systems present hurdles like the 'black box' that challenges understanding and accountability. Scalability, compliance, and cost prompt differentiation of these approaches as well. Traditional methods can sometimes become problematic as data size increases, while AI approaches work well with increased complexity. While the first factor is a set of performance measures that relate to the company's actual performance, the second relates to compliance with acceptable regulatory and ethical standards. Traditional mechanisms follow institutional practices but may be rigid in accommodating new practices, while new IT mechanisms, though flexible, may bring in biases and privacy issues. Finally, cost-efficiency contrasts the extremity of traditional systems when it comes to using labor with the relatively high initial investment in the case of AI-driven solutions. However, All these criteria offer a sound platform for understanding their suitability or otherwise in dynamically transforming IT environments.

4.2.6. Real-World Case Studies

AI success stories in data governance all show that the technology can revolutionize the ways of working. For instance, Mastercard has adopted AI by analyzing specific patterns to improve data protection and conformance to data laws while undertaking international transactions. Similarly, IBM uses AI in Watson to help organizations adhere to GDPRs in managing data privacy. [13] These examples demonstrate how AI can reduce the time taken to perform difficult governance work and how the work can be done more accurately. Nevertheless, specific implementation remains more problematic than others. Although Facebook uses AI to prevent radicalization extremism and protect users' data privacy, it has been noted to be biased towards certain aspects, for instance, algorithmic decisions and leakage of sensitive users' information during the Cambridge Analytica scandal. [14] Further, a gender bias was raised when Amazon's AI recruiting tool resulted in problems with machine learning when faced with unbalanced datasets. These cases highlight the need for strong structures and ethical considerations in realizing efficient Artificial Intelligence (AI) in data management.

4.2.7. Future Directions Expansion

Technologies such as Blockchain are changing the shape of Data management by providing improved clarity, security, and credibility. Due to distributed ledgers, Blockchain is a secure technology for preserving data integrity, minimizing unauthorized changes, and increasing accountability. It provides superior data lineage, meaning the ability to trace data's origin, which is very important for compliance and audit purposes. Furthermore, when blockchain is combined with AI, both systems gain complementary functions, such as securely sharing data for AI learning. However, limitations include interoperability and high energy consumption required for blockchain's work. Nonetheless, the unique opportunity of using blockchain technologies to redefine data management makes the integration of blockchain technologies for traditional and AI-based approaches highly beneficial.

4.2.8. The Future of Data Governance

This has made it clear that data governance in the future will involve a mixture of traditional governance and artificial intelligence. There will be continued calls to 'democratize 'AI in that organizations will seek to incorporate the technologies into their data strategies without relinquishing the final say on important business decisions or compliance measures. [5, 9] AI's governance enhancement will support scalable, accurate, and dependable organizations but raises questions about equity and lawful compliance essential to solving.

The outcomes of this systematic review demonstrate that as the execution of modern data ecosystems becomes complex, traditional data governance methodologies must emerge and adapt. AI-enhanced governance presents a viable solution to many corporate governance challenges, but only if it is integrated appropriately into the current and evolving governance frameworks and ethical considerations. The future of data governance would still be a coordination of the two approaches with the ability to govern data while staying compliant, secure, and ethical.

4.2.9. Study Limitations

As to the limitation of this study, it is imperative to recognize that this research gives only a comparative overview of data governance under traditional and AI approaches. First, the study overly depends on the literature to collect information, which might limit the recognition of the latest innovations and issues in the growing application of IoT. Second, due to the relatively recent inception of AI as an independent field and continuous advancements in this and related areas, the task is challenging, and there is no straightforward evaluation method. Another limitation was that only a selected case was used, and as a result, unusual or poorly documented instances may not have been well represented. Moreover, it is mostly theoretical and qualitative and lacks rigorous empirical evidence and references to quantitative standards. Finally, the external validity of conclusions can be limited to institutional and technological differences worldwide. To increase the depth and practical relevance of the findings about data governance in the future, it will be necessary to address certain limitations of the current study.

4.2.10. Interdisciplinary Approach

Law, information science, and ethical considerations should be undertaken as they provide an integrated approach to good data management. Compliance or legal perspective is the core of compliance, and it follows rules and regulations, including GDPR, HIPAA, and the currently evolving AI regulations. [5] This perspective defines responsibility, confidentiality, and measures for removing algorithmic prejudice or misuse of data. Information science offers engineering with a technical approach developed from IT best practices for data storage/management, integration of systems, and application of AI technologies in improving the quality, capacity, and security of the data. Information science in action uses machine learning and blockchain and targets real issues, such as the problem of data silos and real-time data analysis. Ethical considerations guarantee that guidelines affect equality, diversity, and openness to respond to issues like embedding bias, liberty, and social effects. In this way, disparate disciplines coalesce that organizations can harness to create the right governance archetypes, where legal frameworks, technological impetus, and ethical considerations for growth might align to maintain value, stakeholder, and societal integrity.

5. Conclusion

This systematic review also aimed to discuss changes in the data management approach by comparing traditional methods with AI approaches. Classic data management remains relevant for sectors that need rigid compliance with the rules, providing tested procedures and immediate supervision to guarantee data credibility, privacy, and responsibility management.

However, it is unsuitable for large complex systems, changes in requirements, and real-time data management in present-day environments. The possibilities that automation offers, such as the ability to manage large amounts of data and enhance decision-making with the help of AI systems, make us consider AI-driven data governance a promising solution. It improves scalability and flexibility, making it usable and applicable for myriad unstructured data and information flows. At the same time, AI-embedded governance opens issues like the interpretability of AI models, bias and ethnicity in AI, and AI ripeness of the technologies used.It would be safe to predict that the future of data governance will blend the conventional forms of data governance with advanced systems that include the application of artificial intelligence. Managers should proactively adopt AI in organizations, but organization transparency and ethical considerations should not be compromised. Yet, the strengths of AI in real-time processing, compliance, and data quality assurance should not be underestimated. This governance model will be a classic mix that is sufficient to adequately address existing regulations and challenges of current data.

6. Conflicts of Interest

Regarding the publication of this article, the authors have no conflict of interest to report. The study was carried out without any vested interests in the authors, personnel, or pecuniary gain that may influence the study's findings, conclusion, or recommendations. No sources were given preference over others, and the data governance models presented in this paper result from a fair analysis of literature and current practices.

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This research did not receive any special grants from any funding body. The authors performed the primary research without any sponsor's financial contributions from various organizations, commercial entities, or governmental agencies. The authors also take full responsibility for designing, conducting, and analysing the research. Every claim and suggestion in this paper stems from the literature and a critical analysis of existing data governance frameworks.

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