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SURVEY

Impact of a Master Data Management Framework to Trigger Data Governance Maturity: A Systematic Literature Review

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ABSTRACT Data governance plays a crucial role for organizations aiming to improve data quality, security, and compliance, yet research reveals ongoing challenges in implementation, maturity, and the practical effectiveness of current frameworks. Despite the availability of numerous concepts, models, and assessments, their actual impact and relevance remain fragmented and insufficiently explored. This Systematic Literature Review (SLR) investigates how data governance frameworks influence maturity and identifies the factors that drive their effectiveness. Through the synthesis of existing research, the review aims to clarify the relationship between governance frameworks and maturity levels, highlight operational benefits, and examine implementation challenges, ultimately contributing to both academic understanding and practical advancements in data governance. Analyzing the most relevant studies, the review seeks to uncover the main governance mechanisms, frameworks, and trends shaping this field, with a central question in focus: How can a structured master data management framework improve data governance maturity?.

INDEX TERMS Data governance, data governance maturity level, data governance framework.

I. INTRODUCTION

Data governance plays a crucial role in modern organizations, yet its implementation and effectiveness remain subjects of ongoing discussion. As organizations increasingly rely on data for strategic decision-making, compliance, and operational efficiency, several studies have explored how governance frameworks contribute to these objectives. However, key questions remain regarding how structured governance frameworks impact maturity, what challenges organizations face, and how different models compare in practice.

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This Systematic Literature Review (SLR) is designed to investigate these aspects, guided by the following central research question:

A. HOW CAN STRUCTURED MASTER DATA MANAGEMENT FRAMEWORK IMPACT DATA GOVERNANCE MATURITY?

To address this, the study will approach the main question by breaking it down into the following sub questions, better explored most below in topic II. (Materials and Methods):

1) What are the most relevant concepts, standards, and models used as references in data management and governance?
2) Are there standardized organizational data governance frameworks?

3) What are the most widely used maturity models in data governance?
4) What are the key antecedents and impacts on governance maturity?

Preliminary research showed that data governance is becoming an increasingly relevant topic as organizations seek to structure their data management practices in response to evolving business and regulatory demands [1]. The literature suggests that data governance is generally perceived as a set of policies, processes, and structures implemented to ensure data integrity, security, and usability [2]. In relevant studies, organizations often report new challenges, including difficulties in integrating governance strategies with existing systems, maintaining compliance across different jurisdictions, and ensuring governance models remain adaptable to technological advancements [3].

Although preliminary research showed that data governance has been widely studied, existing studies tend to focus on specific aspects such as data quality, metadata management, and security, rather than presenting a comprehensive and standardized approach [4], [5], [6]. Additionally, studies revealed that there is no clear consensus on which frameworks or maturity models are the most effective in practice, as their applicability varies depending on organizational structure, industry, and regulatory landscape [7]. Some research highlights the role of maturity models as a tool for assessing governance evolution, yet their definitions, scope, and applicability remain inconsistent [8], [9].

Governance frameworks also vary significantly, with some models prioritizing regulatory compliance and risk management, while others focus on enhancing data-driven decision-making and aligning governance strategies with business objectives [10], [11]. The effectiveness of these frameworks is often debated, as implementation success depends on multiple factors, including organizational culture, leadership commitment, and existing data management capabilities [12], [13].

To gain a deeper understanding of these issues, this SLR will systematically analyze existing research on governance frameworks and maturity models, aiming to identify trends, challenges, and gaps in the literature [14], [15]. Rather than proposing a new governance framework, this study will examine how different models are applied, assess their reported benefits and limitations, and explore emerging discussions on governance maturity [16], [17], [18].

By conducting further and deeper analysis, this research seeks to provide a structured overview of the state-of-the-art in data governance, offering insights that can inform both academic discourse and practical governance strategies emphasizing the importance of measuring data governance maturity levels to identify areas for improvement and track progress.

II. MATERIALS AND METHODS

Researching Data Governance adoption models requires the application of suitable data and methodologies to gain meaningful insights into the factors that influence, and the processes involved in adopting this practice. This study aims to contribute to the scientific community by providing a deeper understanding of Data Governance implementation, utilizing frameworks and measuring the impact on maturity levels, while also addressing gaps identified in literature. Additionally, assessing Data Governance maturity and establishing key performance indicators (KPIs) are essential for evaluating an organization's progress and effectiveness in implementing Data Governance frameworks. Understanding the antecedents—such as organizational culture, leadership support, and existing data management practices—and the impacts of applying a Data Governance framework is crucial for achieving higher maturity levels. These data and research approaches are fundamental for thoroughly understanding how organizations make decisions and behave regarding the implementation of Data Governance. In the following section, we will explore the materials and methods commonly utilized in this area of study, with a particular focus on frameworks and measuring maturity levels for data governance [4], [16], [19].

A systematic literature review is meticulously designed to gather and analyze empirical data that fulfills established eligibility criteria, aiming to address a well-defined research question. This comprehensive process employs a range of rigorous techniques and standardized procedures to minimize potential biases, ensuring that the outcomes are both credible and reliable. By thoroughly synthesizing existing studies, a systematic literature review seeks to provide a robust and trustworthy foundation for advancing knowledge and understanding within the relevant field. Through its structured and methodical approach, it endeavors to uncover meaningful patterns, identify gaps in the current literature, and offer insightful conclusions that contribute significantly to scholarly discourse [15], [23].

Kitchenham's methodology, developed by Barbara Kitchenham, is a systematic and structured framework specifically designed for conducting Systematic Literature Reviews (SLRs) in the field of software engineering. This methodology encompasses all essential stages of conducting a systematic review, from developing well-defined research questions to selecting studies, extracting data, assessing the quality of evidence, and presenting results in a standardized format. By outlining clear research objectives and formulating specific questions, Kitchenham's approach ensures focused and researchable inquiries. The methodology includes developing a detailed review protocol with explicit inclusion and exclusion criteria, comprehensive literature searches across multiple databases, and a rigorous study selection process involving title, abstract, and full-text screening.

Furthermore, Kitchenham's methodology emphasizes thorough quality assessment of the included studies using standardized evaluation tools and standardized data extraction through predefined forms to capture essential information consistently. The synthesis of findings is conducted in a coherent manner, employing both qualitative and quantitative analyses where applicable. This structured approach promotes methodological rigor, transparency, and reproducibility, facilitating replication, critical evaluation, and effective synthesis of evidence. By adhering to Kitchenham's systematic framework, this systematic literature review ensures high quality, reliability, and transparency, making the results accessible and comprehensible to researchers, practitioners, and the broader scientific community. Kitchenham's guidelines have been instrumental in advancing knowledge within software engineering by identifying research gaps and providing evidence-based conclusions that inform future research and practice [15], [21].

Kitchenham's methodology for Systematic Literature Reviews (SLRs) is renowned for its adaptability across various research domains beyond its original application in software engineering. In her foundational works, Kitchenham emphasizes the framework's structured yet flexible nature, allowing researchers to customize the review process to meet the specific demands of different fields [21]. This adaptability is facilitated through the clear definition of research questions, the establishment of tailored inclusion and exclusion criteria, and the development of comprehensive search strategies that can be modified to suit diverse disciplines such as data governance. By providing a detailed and systematic approach, Kitchenham's methodology ensures methodological rigor and transparency, which are crucial for conducting reliable and reproducible SLRs in any area of study. Consequently, Kitchenham's methodology was chosen for this SLR on the data governance field due to its proven effectiveness in facilitating comprehensive reviews, enabling the identification of effective frameworks, and supporting the synthesis of best practices tailored to the unique challenges of data governance.

Methodology selected, planning done, now it's time to move on to the next phases, and this SLR will lead to the second and third phases of Kitchenham's guidelines, which represent the conducting and reporting that is in fact the scope of this document, as illustrated below in Figure 1.

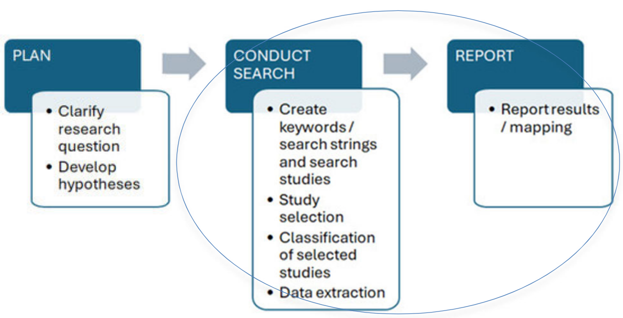

FIGURE 1. Conceptual Mapping for Guideline [20].

A. RESEARCH QUESTIONS

For Kitchenham [21], the critical issue in any systematic review is to ask the right question. Is it meaningful and important to practitioners as well as researchers? - Will it lead either to changes in current practice or to increased confidence in the value of current practice? – Will it identify discrepancies between commonly held beliefs and reality?

Hence, based on the topic of study for this SLR the following main question will be our starting point and will guide us through the research:

1) How can a structured master data management framework impact data governance maturity? *[ans. III.Results – maturity level; consequences]*

However, this question is very broad, and answering it becomes a very difficult task without breaking it down into smaller questions that can help us understand and clarify the topic in smaller parts, while still allowing us to collectively find an answer to the main question. These questions would be:

2) What are the most relevant concepts, standards and models used as guides regarding data management and data governance? *[ans. III.Results – definitions; synthesis of studies and key discoveries]*

3) Are there standard organizational data management and government frameworks? *[ans. III.Results – reference frameworks]*

4) What are the most relevant maturity models used in data management and governance? *[ans. III.Results – maturity models overview; maturity level]*

5) What are the antecedents and potential impacts on data maturity level? *[ans. III.Results – consequences]*

B. CONDUCTING PHASE

1) REPOSITORY SELECTION

At the beginning of the research, we formulated a detailed search strategy for the records. We prioritized accessing the content of five designated and renowned repositories and, when necessary, included pertinent records from additional relevant sources, which we refer to as others. The specific repositories used are detailed in Table 1.

TABLE 1. List of online repositories.

IEEE Xplore - https://ieeexplore.ieee.org/
Springer - https://www.springer.com/
ScienceDirect- https://www.sciencedirect.com/
ACM DL - https://dl.acm.org/
Semantic Scholar - https://www.semanticscholar.org/

2) KEYWORD SELECTION

The keywords are fundamental in conducting a Systematic Literature Review (SLR) as they determine the effectiveness and comprehensiveness of the search strategy. Careful selection of relevant keywords ensures that the most pertinent studies are identified, accurately reflecting the research concepts and objectives. Kitchenham [21] emphasizes that keywords should be derived directly from the research questions and the main topics investigated, using terms that capture the essence of the subject matter. Furthermore, search strings play a crucial role in operationalizing the keywords within the selected databases. Based on the research questions, we elaborate a set of keywords to search in the sources selected above in table 1, then prepared the most common string of searching to be used, represented in sequence by the following tables 2 and 3.

TABLE 2. Keywords used in research.

"Data Governance"
"Information Governance"
"Data Governance Framework"
"Data Governance" "Maturity"

TABLE 3. Search strings.

intitle:"Data Governance Framework" OR intitle:"Data Governance Maturity"
("Data Governance" OR "Information Governance") AND ("Framework" OR "Maturity")

3) PRIMARY INCLUSION/EXCLUSION CRITERIA

In Kitchenham's guidelines [21] for systematic literature reviews, primary inclusion and exclusion criteria are essential to ensure the selection of relevant and high-quality studies. Inclusion criteria focus on studies directly addressing research questions, published within a defined timeframe, in reputable sources, and typically in a specific language, prioritizing empirical research and methodological rigor. Exclusion criteria eliminate studies that are irrelevant, duplicates, of low quality, inaccessible, or lacking empirical evidence. Together, these criteria streamline the selection process to ensure the review is comprehensive, reliable, and aligned with its objectives. The screening and exclusion of articles are vital steps in conducting a Systematic Literature Review (SLR). These processes ensure that only the most relevant and high-quality studies are included, thereby enhancing the validity and reliability of the review's findings. By applying predefined inclusion and exclusion criteria, researchers can filter out articles that do not directly address the research questions or meet methodological standards. Additionally, removing duplicates and excluding studies outside the review's scope helps minimize bias and prevent information overload [21]. This selection of the criteria was based on the definitions and requirements described respectively in Tables 4 and 5. Defining ideal criteria for a Systematic Literature Review (SLR), such as an appropriate time frame, presents a constant methodological challenge—particularly in dynamic fields like data governance, which combines long-standing conceptual foundations with rapidly evolving technological innovations and regulatory demands. In this review, the decision to restrict the temporal scope to the past ten years was intended to prioritize the most recent studies that align with contemporary organizational contexts. The goal was to focus the analysis on updated frameworks and practices that reflect the current challenges and realities faced by organizations in managing data effectively.

However, this temporal delimitation also introduced certain limitations. As noted by Kitchenham [15], exclusion criteria, if not carefully justified, may lead to bias and compromise the comprehensiveness of the review. In this case, several classical contributions that remain foundational to the field were formally excluded. Notably, the works of Khatri and Brown and Weber were left outside the selected time range, despite their continued influence and essential to understanding the foundations of data governance frameworks. One of the most influential is the work of Khatri and Brown, who made an important distinction between data governance and data management. While data management focuses on the day-to-day execution of data activities, data governance is about who has the authority to make decisions related to data. This includes defining roles, responsibilities, and decision rights within the organization. Their model outlines five key areas where decisions need to be clearly defined:

- *Data principles, which are the general rules and policies that guide how data is handled*
- *Data quality, including who defines what "quality" means and who ensures that those standards are met*
- *Metadata, where it's important to determine who is responsible for defining and maintaining the meaning and structure of data*
- *Data access, which covers who can access specific data and under what conditions*
- *Data lifecycle, involving decisions about how long data is kept, when it is archived, and when it should be deleted*

This framework is still highly referenced because it helps organizations clearly separate governance from operational management and focus on decision-making as the core of governance.

Another important contribution comes from Weber, who suggested a more flexible approach to data governance. Instead of proposing a single model that fits all organizations, Weber argued that governance should adapt to each organization's context. This includes considering factors like company size, culture, business goals, and regulatory environment. For instance, a bank operating under strict regulations might require centralized governance, while a tech company working in a fast-moving environment might benefit from a more distributed approach.

This idea becomes even more relevant when we look at recent frameworks like Data Mesh, which are built on decentralization, autonomy, and domain-oriented data ownership. These characteristics align well with Weber's view that governance must fit the organization's reality. Data Mesh is explored in more detail later in the subsection "Conceptual Frameworks" in Section III – Results. Although these foundational works were not formally included in the SLR due to the defined temporal range, their conceptual contributions remain widely cited in the more recent literature that was analyzed. As such, they are indirectly present in the theoretical underpinnings of this study and continue to shape much of the modern academic and practical discourse in data governance. Abraham et al. [16] also emphasize that overly restrictive methodological boundaries, particularly temporal ones—can hinder the recognition of theoretical developments and obscure the field's evolution over time. They advocate for strategies that integrate both historical and emerging perspectives to foster a more holistic understanding of the discipline.

In summary, while the time frame adopted in this review was necessary to ensure alignment with present-day challenges and innovations in data governance, it is important to acknowledge its limitations. Future research efforts should consider complementing temporally focused reviews with broader historical analyses to fully capture the conceptual depth and evolution of governance frameworks.

TABLE 4. Inclusion criteria.

Criteria	Description
CI-01	*Relevance of record:* Studies that directly address the established research questions or objectives.
CI-02	*Type of the record:* Primary studies that use empirical methods, such as experiments, case studies, or systematic reviews related to the topic
CI-03	*Recent and Updated:* Studies published within a relevant time frame (e.g., within the last ten years), ensuring the evidence is up to date.
CI-04	*Methodological Quality:* Studies that follow appropriate scientific rigor, with clearly described and justified methodologies.

TABLE 5. Preliminary exclusion criteria.

Criteria	Description
CE-01	*Irrelevance to the Topic:* Studies that do not address the research questions or fall outside the defined thematic scope.
CE-02	*Publication Language:* Studies published in languages other than those stipulated for the review (English).
CE-03	*Focused on a Branch or company:* Studies that are turned into a single branch or company and not easily replicable to others scope.
CE-04	*Duplicated or Redundant records:* Title or context duplicated studies must be eliminated and prioritized by the most recent ones.

Therefore, these requests could be obtained through the following criteria listed below:

- *Last decade only*
- *Publications in English*
- *Non-Duplicated titles/Authors*
  - *Eliminate articles focused on a specific branch or company and/or short papers.*
  - *Eliminate NON-RELEVANT matters or subject based on title and/or abstract*

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4) SEARCHES CONDUCTION DETAILED

The study was conducted using two primary methods: direct searches within repositories utilizing the "advanced search" feature when available, and software used is the latest version of Harzing's Publish or Perish software at https://harzing.com. For the latter, a maximum of 500 results per keyword was set, focusing on publications from 2014 to 2024. This approach yielded a total of 2,500 records.

Subsequently, only studies published in English were selected, then duplicate titles were removed, and all titles deemed irrelevant to the research, such as those related to specific branches or companies were excluded. This cleaning action resulted in a set of 680 papers that would be further analyzed.

AI-powered tools applied to PDF reading can automate important phases of the systematic review process, particularly in identifying and extracting data from articles. These tools significantly reduce the amount of reading required by providing automated summaries and highlighting the most relevant sections. At the same time, they maintain or even increase the accuracy and sensitivity in study selection, allowing human judgment to focus on final decisions, optimizing time and effort [22], [23].

Hence, by utilizing the AI-powered tool AskyourPDF found at https://askyourpdf.com, the abstracts of each record were examined in batches, and those addressing identical or irrelevant topics were discarded prioritizing the most recent ones. This rigorous filtering process resulted in a preliminary collection of 341 records detailed in Table 6. This allowed for a deeper understanding of the studies' contributions and ensured that only those providing robust and reliable insights were included.

TABLE 6. Remaining records per repositories.

Repository	Records
IEEE Xplore	31
Springer	8
ScienceDirect	17
ACM DL	51
Semantic Scholar	128
Non-indexed academic literature	34
Technical documentation	40
Conceptual models	32
TOTAL	*341*

5) QUALITY CONTROL DETAILED

In line with Kitchenham's guidelines [21], some of the key quality criteria that should be considered in an SLR include methodological rigor, transparency in data collection and analysis, clarity of research objectives, and consistency in addressing the research questions. These criteria help in filtering studies, refining the scope of the review, and ensuring that the final selection of studies provides reliable answers to the research questions. A comprehensive list of these criteria, as applied in this review, detailed in Table 7.

TABLE 7. Quality criteria.

Criteria	Description
CQ-01	*Generalizability of Findings:* Assesses whether the study's results can be generalized beyond the specific sample or context, providing broader applicability to the research field.
CQ-02	*Contribution to Knowledge:* Evaluates whether the study makes a meaningful contribution to the existing body of knowledge, either by filling a gap, proposing new theories, or challenging established ideas.
CQ-03	*Bias and Limitations:* Assesses whether the study acknowledges and addresses potential biases and limitations, ensuring transparency and reducing the risk of misleading results.
CQ-04	*Validity of Conclusions:* Examines whether the conclusions drawn in the study are adequately supported by the data and analysis, ensuring the findings are reliable and valid.

After applying the quality control criteria listed in table 7 above, using the AI-Powered tool AskyourPDF a refined list of records was selected when all the criteria were met. We then could assure the highest standards of scientific rigor and relevance remained, reducing the records from 341 to 51.

The distribution of results based on quality criteria, illustrated below in Table 8, helps to highlight which studies are the most reliable and provide the strongest evidence, ensuring that the final analysis of the review is grounded in high-quality sources. Studies that score lower on essential criteria, such as data validity or bias minimization, may still be included in the analysis but should have less influence on the overall conclusions. This process, as emphasized by Kitchenham, is crucial for ensuring that the review's findings are accurate, trustworthy, and transparent, thereby promoting its replicability and external validity of the [15] and [21].

TABLE 8. Records found in the repositories after QA - Final.

Repository	Records
IEEE Xplore	8
Springer	9
ScienceDirect	2
ACM DL	3
Semantic Scholar	22
Other	7
TOTAL	*51*

Distributing the records based on the most relevant quality criterion per study, as represented in Table 9 below, we can observe that the attempt to create something generic, reproducible, and applicable in various situations and different ways is the most prevalent approach in the studies, accounting for approximately 35.5% of the cases. It is evident that this is the most prominent and significant characteristic for most of the researchers analyzed. We can also get an idea of the distribution of the studies by year in Figure 2, below.

TABLE 9. Records by strongest quality criteria.

Criteria	Description	# Records
CQ-01	Generalizability of Findings	10
CQ-02	Contribution to Knowledge	16
CQ-03	Bias and Limitations	13
CQ-04	Validity of Conclusions	12

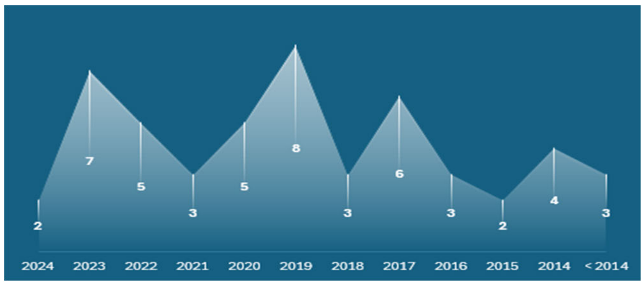

FIGURE 2. Distribution of Records publication per year.

The screening process followed inside the tool AskyourPDF was structured in this sequence:

- *Document upload: All retrieved articles were uploaded to the platform for full-text access and thematic exploration.*
- *Question-driven filtering: Specific questions were used to assess each article's relevance to the objectives of this review.*
- *Exclusion of conceptual duplicates: When multiple studies covered the same concepts, only the most comprehensive, up-to-date, or methodologically rigorous versions were retained.*
- *Removal of studies with limited scope: Articles restricted to a single case, organization, or non-generalizable context were excluded based on CQ-01 (Generalizability of Findings).*
- *Application of exclusion criteria: Additional filters included:*
- *CQ-02 (Contribution to Knowledge): Studies lacking clear theoretical or empirical contribution were removed.*
- *CQ-03 (Bias and Limitations): Studies that failed to acknowledge their limitations or presented clear methodological bias were excluded.*
- *CQ-04 (Validity of Conclusions): Studies with weak or unsupported conclusions, not clearly grounded in data or analysis, were also excluded.*

- *Final organization: Remaining articles were organized for full-text review, data extraction, and categorization aligned with the core research themes.*

For record-keeping and historical purposes, Table 10 below lists all 51 final studies considered in this research. Additionally, Table 11 illustrates the relevance of the most cited authors, along with their year of publication and the respective number of citations. This ordination by citation helped to prioritize the reading and as a basis for "good to have" and "must have" of the other studies with fewer citations.

Briefly and graphically, the whole screening process can be represented by Figure 3 below.

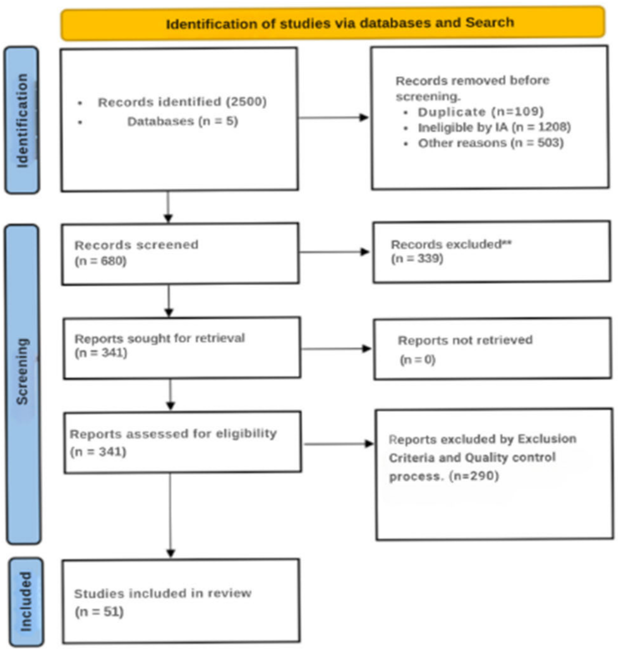

FIGURE 3. Screening process summary.

In conclusion, the meticulous screening process and rigorous quality control, grounded in Kitchenham's guidelines, facilitated a systematic and thorough evaluation of the literature. By adhering to this structured methodology, we ensured that only the most relevant and high-quality studies were incorporated into the review, thereby significantly enhancing the credibility and reliability of the findings. This process was essential in excluding irrelevant or low-quality studies, enabling the review to focus solely on evidence that meaningfully contributes to addressing the research questions. The precision of the screening phase played a critical role in minimizing bias, ensuring transparency, and upholding a replicable methodology throughout the study. This comprehensive approach laid a solid foundation for deriving meaningful and robust discoveries. All this diligent work has culminated in the uncovering of valuable insights and knowledge, which are presented and further elaborated in the following section, Results, where the key findings of this extensive review are outlined [21].

TABLE 10. List of records to be extracted.

Author	Title
Abraham, Rene; Schneider, Johannes; vom Brocke, Jan	Data governance: A conceptual framework, structured review, and research agenda
Akoka, Jacky; Comyn-Wattiau, Isabelle	Evaluation of Big Data Governance - Combining a Multi-Criteria Approach and Systems Theory
Alromaih, Nouf; Albassam, Hend; Al-Khalifa, Hend	A proposed checklist for the technical maturity of open government data: an application on GCC countries
Al-Ruithe, Majid; Benkhelifa, Elhadj	Analysis and Classification of Barriers and Critical Success Factors for Implementing a Cloud Data Governance Strategy
Asih, Sinta Nur; Nabila, Rusyda; Ismed, Istidana Harjanti; Fitriani, Widia Resti; Hidayanto, Achmad Nizar; Yudhoatmojo, Satrio Baskoro	Evaluation of Data Operations Management Maturity Level using CMMI in a State-Owned Enterprise
Ballard, Chuck	Information governace principles and practices for a big data landscape
Bao, Jie; Geng, Xiaozhong; Yu, Ping	A Data Governance Model based on Data Value Analysis under the Framework of Digital Economic
Belghith O, Skhiri S, Zitoun S, Ferjaoui S.	Survey of Maturity Models in Data Management. In: 2021 IEEE 12th International Conference on Mechanical and Intelligent Manufacturing.
Bento, Patricia; Neto, Miguel; Corte-Real, Nadine	How data governance frameworks can leverage data-driven decision making: A sustainable approach for data governance in organizations
Brahmantara, Randy Prima; Hutapea, Destri Yanti; Ruldeviyani, Yova	Evaluation on Data Operations Management using CMMI and DMBOK: BDPJN Case Study
Brous, Paul; Herder, Paulien; Janssen, Marijn	Governing Asset Management Data Infrastructures
Bugbee, Kaylin; Ramachandran, Rahul; Kaulfus, Aaron; Le Roux, Jeanne; Peng, Ge; Smith, Deborah; Gurung, Iksha; Acharya, Ashish; Christman, Jerika	Enabling Dynamic Data Governance in Science: Design, Implementation, and Future Directions of the Modern Data Governance Framework
A. G. Carretero, F. Gualo, I. Caballero, M. Piattini	MAMD 2.0: Environment for data quality processes implantation based on ISO 8000-6X and ISO/IEC 33000
Chanyachatchawan, Sapa; Nasingkun, Krich; Tumsangthong, Patipat; Chata, Porntiwa; Buranarach, Marut; Socharoentum, Monsak	Design and Implementation of a Data Governance Framework and Platform: A Case Study of a National Research Organization of Thailand
Cupoli, Patricia	DAMA-DMBOK2 Framework
DAMA International	DAMA-DMBOK: Data Management Body of Knowledge
Duzha, Armend; Alexakis, Emmanouil; Kyriazis,	From Data Governance by design to Data Governance as a Service: A

TABLE 10. *(Continued.)* List of records to be extracted.

Author	Title
Dimosthenis; Sahi, Louis Fortune; Kandi, Mohamed Ali	transformative human-centric data governance framework
Haneem, Faizura; Kama, Nazri; Taskin, Nazim; Pauleen, David; Abu Bakar, Nur Azaliah	Determinants of master data management adoption by local government organizations: An empirical study
Houser, Kimberly; Bagby, John W.	Next-Generation Data Governance
IDC	The DIGITAL UNIVERSE of OPPORTUNITIES
Ismail, Agung; Suroso, Arif Imam; Hermadi, Irman	Data Governance Design with the DAMA-DMBOK Framework (Case Study: PT. XYZ)
Jang, Kyoung-Ae; Kim, Woo-Je	A Study on Attribute Index for Evaluation of Data Governance
Janssen, Marijn; Brous, Paul; Estevez, Elsa; Barbosa, Luis S.; Janowski, Tomasz	Data governance: Organizing data for trustworthy Artificial Intelligence
Kaewkamol, Porntida	Data Governance Framework as Initiative for Higher Educational Organisation
Khatri, Vijay	Managerial work in the realm of the digital universe: The role of the data triad
Kim, H.Y.; Cho, J.S.	Data governance framework for big data implementation with NPS Case Analysis in Korea
Kitchenham, Barbara	Guidelines for performing Systematic Literature Reviews in Software Engineering
Kitchenham, Barbara	Procedures for Performing Systematic Reviews
Kitchenham, Barbara; Brereton, Pearl	A systematic review of systematic review process research in software engineering
Kurniawan, Dwitama Heryadi; Ruldeviyani, Yova; Adrian, Mohammad Rizky; Handayani, Sutia; Pohan, M. Rizki; Khairunnisa, Rani T.	Data Governance Maturity Assessment: A Case Study in IT Bureau of Audit Board
Kuzio, Jacqueline; Ahmadi, Mohammad; Kim, Kyoung-Cheol; Migaud, Michael R.; Wang, Yi-Fan; Bullock, Justin	Building better global data governance
Legner, Christine; Pentek, Tobias; Otto, Boris	Accumulating Design Knowledge with Reference Models: Insights from 12 Years' Research into Data Management
Lillie, Theresa; Eybers, Sunet	Identifying the Constructs and Agile Capabilities of Data Governance and Data Management: A Review of the Literature

TABLE 10. *(Continued.)* List of records to be extracted.

Author	Title
Lis, Dominik; Arbter, Michael; Spindler, Markus; Otto, Boris	An Investigation of Antecedents for Data Governance Adoption in the Rail Industry—Findings from a Case Study at Thales
Lismont, Jasmien; Vanthienen, Jan; Baesens, Bart; Lemahieu, Wilfried	Defining analytics maturity indicators: A survey approach
MacFeely, Steve; Me, Angela; Fu, Haishan; Veerappan, Malarvizhi; Hereward, Mark; Passarelli, David; Schüur, Friederike	Towards an international data governance framework
Mahanti, Rupa	Data Governance and Data Management Functions and Initiatives
Marcucci, Sara; Alarcon, Natalia Gonzalez; Verhulst, Stefaan G.; Wullhorst, Elena	Mapping and Comparing Data Governance Frameworks: A benchmarking exercise to inform global data governance deliberations
Marshall, Iain J.; Wallace, Byron C.	Toward systematic review automation: a practical guide to using machine learning tools in research synthesis
Mecredy, Graham; Sutherland, Roseanne; Jones, Carmen	First Nations Data Governance, Privacy, and the Importance of the OCAP® principles
Micheli, Marina; Ponti, Marisa; Craglia, Max; Berti Suman, Anna	Emerging models of data governance in the age of datafication
Morabito, Vincenzo	Big Data and Analytics: Strategic and Organizational Impacts
Nielsen, Olivia Benfeldt	A Comprehensive Review of Data Governance Literature
Nielsen, Olivia Benfeldt; Persson, John Stouby; Madsen, Sabine	Why Governing Data Is Difficult: Findings from Danish Local Government
O'Mara-Eves, Alison; Thomas, James; McNaught, John; Miwa, Makoto; Ananiadou, Sophia	Using text mining for study identification in systematic reviews: a systematic review of current approaches
Qi, Xiaoying	Research on Enterprise Data Governance Based on Knowledge Map
Ruslan, Ishak Firdauzi; Alby, Muhammad Fahmi; Lubis, Muharman	Applying Data Governance using DAMA-DMBOK 2 Framework: The Case for Human Capital Management Operations
Saputra, Dimas Agung; Handika, Dika; Ruldeviyani, Yova	Data Governance Maturity Model (DGM2) Assessment in Organization Transformation of Digital Telecommunication Company: Case Study of PT Telekomunikasi Indonesia
Tallon, Paul P.; Ramirez, Ronald V.; Short, James E.	The Information Artifact in IT Governance: Toward a Theory of Information Governance
Wider, Arif; Verma, Sumedha; Akhtar, Atif	Decentralized Data Governance as Part of a Data Mesh Platform: Concepts and Approaches

TABLE 10. ***(Continued.)*** **List of records to be extracted.**

Author	Title
Wulandari, Sari Agustin	Data Governance Maturity Level at the National Archives of the Republic of Indonesia

III. RESULTS: SYNTHESIS OF STUDIES AND KEY DISCOVERIES

This systematic exploratory analysis has brought to light the most important and relevant concepts regarding data governance, its frameworks, applications, and impacts on maturity, as well as the most used maturity models and evaluations. Additionally, it highlights existing gaps and the vast potential of this field to be further explored in search of tools and concepts that can support future academic and practical investigations.

Beginning by addressing the definitions of data governance from various perspectives. Data governance encompasses a spectrum of definitions and applications, deeply rooted in the intricacies of managing an organization's data assets. This essay explores the evolving definitions of data governance, emphasizing its importance in maintaining data integrity, ensuring compliance, and enhancing organizational performance. With the advent of stringent regulatory requirements and the exponential growth of data, the role of data governance has become paramount in modern business practices. The significance of structured data governance approaches is highlighted by the increasing need to address First Nations data sovereignty issues, as detailed by [17], which stresses the importance of governance frameworks that respect community data privacy and ownership.

Data governance is traditionally viewed as the systematic management of data accessibility, usability, integrity, and security in enterprises. Definitions tend to focus on data quality, compliance with regulations, and internal policies that control data usage. Over the years, the framework has expanded from a set of responsibilities and policies to a comprehensive program that includes people, processes, and technologies [16]. In Table 12 below, we can see those definitions across several perspectives.

Data governance proved to be traditionally viewed as the systematic management of data accessibility, usability, integrity, and security in enterprises. Definitions tend to focus on data quality, compliance with regulations, and internal policies that control data usage. Over the years, the framework has expanded from a set of responsibilities and policies to a comprehensive program that includes people, processes, and technologies [16].

The Data Governance Reference Frameworks (DGRF) or simply Frameworks now often incorporate a multidimensional approach, involving not just the management

TABLE 11. **Records by citations.**

Author	Year	Citations
O'Mara-Eves, Alison; Thomas, James; McNaught, John; Miwa, Makoto; Ananiadou, Sophia	2015	700
Abraham, Rene; Schneider, Johannes; Vom Brocke, Jan	2019	678
A. G. Carretero, F. Gualo, I. Caballero, M. Piattini.	2017	535
IDC	2014	515
Tallon, Paul P.; Ramirez, Ronald V.; Short, James E.	2014	445
Marshall, Iain J.; Wallace, Byron C.	2019	436
Morabito, Vincenzo	2015	334
Micheli, Marina; Ponti, Marisa; Craglia, Max; Berti Suman, Anna	2020	263
Lismont, Jasmien; Vanthienen, Jan; Baesens, Bart; Lemahieu, Wilfried	2017	172
Haneem, Faizura; Kama, Nazri; Taskin, Nazim; Pauleen, David; Abu Bakar, Nur Azaliah	2019	138
Brous, Paul; Janssen, Marijn; Krans, Rutger	2020	127
Nielsen, Olivia Benfeldt; Persson, John Stouby; Madsen, Sabine	2019	108
Nielsen, Olivia Benfeldt	2017	94
DAMA International	2017	72
Legner, Christine; Pentek, Tobias; Otto, Boris	2020	66
Ballard, Chuck; Compert, Cindy; Jesionowski, Tom; Milman, Ivan; Plants, Bill; Rosen, Barry; Smith, Harald; Safari, an O'Reilly Media Company	2014	63
Karkošková, Soňa	2023	63
Zhang, Qingqiang; Sun, Xinbo; Zhang, Mingchao	2022	52
Kim, Hee Young; Cho, June-Suh	2017	47
Al-Ruithe, Majid; Benkhelifa, Elhadj	2017	43
Brous, Paul; Herder, Paulien; Janssen, Marijn	2016	43
Cupoli, Patricia	2014	39
Merkus, Jan; Helms, Remko; Kusters, Rob	2019	37
Lillie, Theresa; Eybers, Sunet	2019	27
Thabit, Thabit H.; Ishhadat, Heba S.; Abdulrahman, Omer T.	2020	27
Mecredy, Graham; Sutherland, Roseanne; Jones, Carmen	2018	25
Meer, L. V. D.	2015	21
Khatri, Vijay	2016	20
Wider, Arif; Verma, Sumedha; Akhtar, Atif	2023	15
Lis, Dominik; Arbter, Michael; Spindler, Markus; Otto, Boris	2023	13
Nadal, Sergi; Jovanovic, Petar; Bilalli, Besim; Romero, Oscar	2022	13

TABLE 11. ***(Continued.)*** **Records by citations.**

Author	Year	Citations
Kuzio, Jacqueline; Ahmadi, Mohammad; Kim, Kyoung-Cheol; Migaud, Michael R.; Wang, Yi-Fan; Bullock, Justin	2022	13
O'Sullivan, Katherine; Lumsden, Joanne; Anderson, Caroline; Black, Corri; Ball, William; Wilde, Katie	2024	11
Bento, Patricia; Neto, Miguel; Corte-Real, Nadine	2022	11
Asih, Sinta Nur; Nabila, Rusyda; Ismed, Istidana Harjanti; Fitriani, Widia Resti; Hidayanto, Achmad Nizar; Yudhoatmojo, Satrio Baskoro	2019	10
Alromaih, Nouf; Albassam, Hend; Al-Khalifa, Hend	2016	10
Kurniawan, Dwitama Heryadi; Ruldeviyani, Yova; Adrian, Mohammad Rizky; Handayani, Sutia; Pohan, M. Rizki; Khairunnisa, Rani T.	2019	9
MacFeely, Steve; Me, Angela; Fu, Haishan; Veerappan, Malarvizhi; Hereward, Mark; Passarelli, David; Schüür, Friederike	2022	8
Saputra, Dimas Agung; Handika, Dika; Ruldeviyani, Yova	2018	6
Duzha, Armend; Alexakis, Emmanouil; Kyriazis, Dimosthenis; Sahi, Louis Fortune; Kandi, Mohamed Ali	2023	6
Ruslan, Ishak Firdauzi; Alby, Muhammad Fahmi; Lubis, Muharman	2023	6
Marcucci, Sara; Alarcon, Natalia Gonzalez; Verhulst, Stefaan G.; Wullhorst, Elena	2023	5
Wong, Doris Hooi-Ten; Maarop, Nurazean; Samy, Ganthan Narayana	2020	4
Akoka, Jacky; Comyn-Wattiau, Isabelle	2019	4
Bao, Jie; Geng, Xiaozhong; Yu, Ping	2022	3
Kaewkamol, Porntida	2022	3
Marcucci, Sara; Alarcón, Natalia González; Verhulst, Stefaan G.; Wüllhorst, Elena	2023	3
Brahmantara, Randy Prima; Hutapea, Destri Yanti; Ruldeviyani, Yova	2021	2
Houser, Kimberly; Bagby, John W.	2023	2
Mahanti, Rupa	2021	2
Wulandari, Sari Agustin	2020	1

TABLE 12. **Definitions for data governance perspectives.**

Perspective	Definition	Source
Adaptive Definition	Discusses data governance as a dynamic and adaptable process shaped by the changing needs and structures within organizations.	[16]
Organizational Function	Explores data governance as a crucial organizational function that aligns data management strategies with business objectives.	[19]
Framework Perspective	Describes data governance frameworks as structured systems designed to control data assets effectively, ensuring both compliance and strategic use.	[11]
Cross-Functional Framework	Views data governance as a cross-functional framework that integrates various departmental efforts across an organization.	[16]
Procedures and Policies	Outlines standardized procedures and policies that form the backbone of effective data governance practices.	[1]
Standards for Data Quality and Management	Focuses on the importance of establishing and maintaining high standards for data quality and management to ensure organizational data integrity.	[12]
Privacy and Confidentiality	This source likely discusses the critical aspects of data governance concerning the protection of privacy and confidentiality. It would cover how data governance frameworks address the challenges of managing personal and sensitive information in compliance with legal and ethical standards, ensuring that data is used responsibly and securely within organizations.	[24]
Compliance Monitoring	Discusses the mechanisms and tools used in monitoring and ensuring compliance with relevant data protection laws and regulations.	[25]

of data but also the governance of related technologies and business processes. This broader perspective helps organizations understand and ensure that data governance aligns with business objectives, providing clear metrics for data quality and the evaluation of governance initiatives. The key elements of a robust data governance framework include [1], [18], [19] and [26]:

- *Data Quality Management: Ensuring accuracy, timeliness, completeness, and consistency of data. This involves setting and enforcing data quality standards to ensure that organizational data is accurate, complete, timely, and consistent. Effective data quality management helps businesses make more reliable decisions and improves operational efficiency.*
- *Data Security and Privacy: Protecting data from unauthorized access and ensuring compliance with privacy laws. This also involves implementing robust access controls and audit trails to monitor data usage and prevent data breaches.*
- *Metadata Management: Managing the metadata to understand data origins, uses, and transformations. Developing a metadata repository to store information about data assets is crucial. This includes descriptions of data sources, data structures, and the relationships between data elements, which are crucial for effective data management and usage.*
- *Data Operations Management: Operational oversight includes data archiving, backup, and business continuity planning. This element ensures that data remains secure, accessible, and reliable over time, supporting operational needs and compliance requirements.*

- *Regulatory Compliance: Adhering to relevant laws and regulations that affect data usage. This includes maintaining data in compliance with legal and regulatory frameworks, ensuring that the organization meets its external obligations.*

A. CONCEPTUAL FRAMEWORKS

In the development of conceptual frameworks for Data Governance, a comparative understanding of the leading reference models is essential. This subsection explores three influential approaches — DAMA-DMBOK, DCAM, and Data Mesh — comparing them in terms of scope, maturity support, and real-world applicability.

In terms of scope, DAMA-DMBOK (Data Management Body of Knowledge), developed by DAMA International, provides a comprehensive and structured reference framework that covers all major areas of data management, including governance, architecture, quality, security, storage, and metadata [1], [30]. It is widely accepted as a foundational standard in both academic and professional environments. DCAM (Data Management Capability Assessment Model), developed by the EDM Council, offers a more pragmatic and implementation-oriented approach, emphasizing capabilities, controls, and organizational alignment [51]. It is particularly designed to support maturity assessments and regulatory compliance in complex organizational settings. Meanwhile, Data Mesh, proposed by Zhamak Dehghani, presents a more organizational and cultural scope, promoting a decentralized data architecture where data ownership is distributed across business domains, encouraging self-service data platforms and federated governance [26].

In terms of maturity support, DAMA-DMBOK provides conceptual guidelines that can indirectly support maturity assessments by formalizing data management functions. Although it does not include a native maturity model, its broad adoption enables it to be mapped onto external assessment frameworks [1], [32]. On the other hand, DCAM was explicitly designed as a maturity assessment tool. It includes detailed criteria and scoring mechanisms that allow organizations to evaluate their current capabilities and define developmental roadmaps, especially in regulated sectors [51]. Data Mesh does not feature a formal maturity model in the traditional sense. However, its conceptual principles enable agile and incremental evolution of data capabilities. Maturity in the context of Data Mesh is assessed based on domain autonomy, organizational alignment, and culture rather than linear stages [26].

In terms of real-world applicability, DAMA-DMBOK is deeply rooted in both industry and academia, serving as a foundation for implementing data governance programs across various sectors. It is used in training, certification, and organizational structuring, offering a common vocabulary and structured practices for data professionals [1], [30], [33]. DCAM is widely adopted in the financial services, healthcare, and government sectors, where data regulation requires measurable compliance and maturity indicators [51]. Its pragmatic structure supports deployment in contexts demanding auditability and standardization. Data Mesh has gained popularity among digitally native and data-driven companies, particularly in the technology and software sectors. Its scalability, agility, and alignment with DevOps practices and microservices architectures make it attractive for modern data infrastructures [26]. However, its adoption requires significant cultural changes and organizational engagement.

Concluding that, in this way, considering its consolidated relevance, comprehensive approach, and strong acceptance in both market and academic spheres, DAMA-DMBOK stands out as the most appropriate central axis for this investigation. Its established structure, which integrates all essential areas of data management, provides a clear, consistent, and widely recognized methodological foundation.

Even so, we acknowledge that alternative models such as DCAM and Data Mesh offer significant and complementary contributions. DCAM stands out for its practical orientation and applicability to maturity and organizational self-assessment models, being particularly effective in regulatory and compliance-driven environments. Data Mesh, with its focus on decentralization and scalability, is highly aligned with digital, agile, and distributed organizations.

Therefore, although the research is structured based on DAMA-DMBOK as the main conceptual reference, the practical contributions and distinctive features of DCAM and Data Mesh will be incorporated in future stages, broadening the scope of the analysis and enabling the limitations of the main model to be overcome, as illustrated in Figures 4 to 7 [1], [30], [26], and [51].

Framework	DAMA-DMBOK	Data Mesh	DCAM
Origin	DAMA International (Data Management Association)	Concept created by **Zhamak Dehghani**	EDM Council (Enterprise Data Management Council)
Focus	Comprehensive guide to data management and governance	**Decentralized** governance, domain-driven data ownership	**Maturity model** for assessing and evolving data governance
Objective	Establish a **structured and standardized** approach to data governance	Distribute and delegate governance **to data domains**	**Measure and enhance** data governance maturity
Approach Type	**Centralized** and structured, covering all aspects of data management	**Decentralized**, with autonomy given to domains	**Capability-based maturity model**, with practical metrics and evaluations

FIGURE 4. Overview of data governance framework and models.

Despite the various justifications presented above, incorporating DAMA DMBOK into data governance practices involves aligning data management activities with business strategies and objectives, as demonstrated by various sectors showing significant improvements in data handling, compliance, and strategic use of data. This integration ensures the reliability, consistency, and security of their data assets,

Context	Best Option
Traditional enterprise with strong regulatory compliance needs	✅ DAMA-DMBOK
Modern, distributed organization (e.g., startups, multinational agile companies)	✅ Data Mesh
Organizations seeking to measure and improve governance maturity	✅ DCAM

FIGURE 5. Best choice by context.

Feature	DAMA-DMBOK	Data Mesh	DCAM
Structure	Set of **principles and best practices** for data governance	Distributed model with **domain responsibility** for data	Maturity model based on **capabilities and governance evolution**
Data Governance	Centralized, with well-defined roles (e.g., Data Steward, Data Owner)	Each domain governs its own data	Based on **governance maturity and structured assessments**
Data Architecture	Traditional, based on **ETL, Data Warehouses, and Data Lakes**	Decentralized, data as **products** (Data Products)	Adaptable to various architectures
Scalability	Works well in **traditional organizational structures**	Better suited for **agile and distributed organizations**	Focused on **organizational scaling and continuous improvement**
Automation	Not directly focused on automation	**Highly reliant on automation** (APIs, distributed services)	Evaluates and recommends automated governance processes
Data Quality Management	Defines metrics, processes, and policies for **ensuring data quality**	Each domain is responsible for its own **quality control**	Includes quality as a **maturity evaluation criterion**
Security & Compliance	Covered **in detail and comprehensively**	Each domain applies **its own security and compliance rules**	Includes compliance as an evaluation factor

FIGURE 6. Overview of data governance framework and models.

	DAMA-DMBOK	Data Mesh	DCAM
✅ Pros	✅ **Well-established and structured model**	✅ Scalable for **modern, agile, and distributed enterprises**	✅ **Continuous evaluation and measurable improvement**
	✅ Excellent for **compliance and regulatory alignment**	✅ Autonomy and **local data ownership responsibility**	✅ Focused on **governance process enhancement**
	✅ Best suited for **auditability and security**	✅ Reduces **friction between IT and business teams**	✅ Adaptable to various **frameworks and standards**
❌ Cons	❌ **Rigid** for modern, agile enterprises	❌ Requires **strong automation and a mature data culture**	❌ Needs to be integrated into a broader governance framework
	❌ High complexity in implementation	❌ **Can create data silos** if not well-implemented	❌ **Requires investment in regular maturity assessments**

FIGURE 7. Pros. & Cons.

ultimately enhancing overall performance and competitiveness [1].

The landscape of data governance continues to evolve as technology advances and regulatory environments become more complex. Organizations must adapt their data governance frameworks to accommodate emerging technologies such as artificial intelligence and machine learning, which pose new challenges and opportunities for data management, for example.

The integration of comprehensive data governance frameworks into organizational strategy is crucial for building a resilient foundation for data management. As organizations continue to recognize the strategic value of data, the role of data governance as a critical function will expand, further embedding its principles into the fabric of organizational processes and culture [19].

Data governance frameworks significantly contribute to improving the maturity levels of data assets and user competencies within an organization. Maturity in data governance refers to the extent to which data management practices are formalized and integrated into the daily operations and strategic planning of an organization. Higher maturity levels indicate more sophisticated, predictable, and effective data management practices. Assessing the maturity level of data governance functions is crucial for identifying gaps and planning improvements. By leveraging frameworks such as the Stanford Data Governance Model, organizations can systematically enhance their governance practices, thus achieving higher maturity levels [27].

The adoption of data governance within organizations is driven by several antecedents, including the need for enhanced data quality, security demands, regulatory compliance, and the strategic use of data for business innovation [28]. These antecedents set the stage for a comprehensive approach to managing an organization's data assets effectively.

The impacts of implementing data governance are profound, ranging from improved decision-making and operational efficiencies to enhanced compliance and risk management. Data governance provides a structured framework to capitalize data as a strategic asset, thereby supporting business objectives and driving innovation.

The scope of data governance extends across the entire organization, influencing various departments from IT to marketing, finance, and operations. It encompasses all aspects of data management, including data quality, data access, data lifecycle management, and data security.

Consequently, the successful implementation of data governance leads to several positive outcomes for organizations. It enhances the maturity level of data management practices, making them more systematic and mature. This transformation supports better compliance with data protection regulations and improves the overall reliability and value of data assets. Organizations become more agile, with the ability to respond quickly to market changes and opportunities, thereby gaining a competitive edge [28].

For instance, among other models cited in the studies the Capability Maturity Model Integration (CMMI) is a widely recognized framework designed to assist organizations in enhancing their processes and overall performance. This is an example of a framework that helps organizations improve their processes and performance and measure the maturity level. It provides a set of best practices for process improvement across various areas such as software development, systems engineering, and project management. CMMI is structured into maturity levels, each representing a level of organizational process maturity and capability [29]. Crossing these maturity levels and their parameters with a standard and structured data governance framework, analyzing the antecedents and consequences after this implementation is the goal and primary question to be answered in this research.

In essence, the research and relevant material explored in this SLR come to light as the landscape of data governance continues to evolve as technology advances and regulatory environments become more complex. Organizations must adapt their data governance frameworks to accommodate emerging technologies such as artificial intelligence and machine learning, which pose new challenges and opportunities for data management.

The integration of comprehensive data governance frameworks into organizational strategy is crucial for building a resilient foundation for data management. As organizations continue to recognize the strategic value of data, the role of data governance as a critical function will expand, further embedding its principles into the fabric of organizational processes and culture.

The current state of understanding regarding data governance was analyzed based on the compilation of reviewed literature. A possible approach, compiling all the studies and models, could be represented and aligned with the structure depicted in Figure 8 and Figure 9, outlining a sample of a conceptual framework. Each aspect of this framework is meticulously examined to offer a comprehensive insight. Initiating the discussion by elaborating on the fundamental dimension, focusing primarily on governance mechanisms. Subsequently, delving into the organizational, data, and domain scopes, elucidating how these aspects interact with governance mechanisms. Following this, the antecedents that play a pivotal role in shaping the establishment and configuration of data governance practices. Finally, encapsulate this section by exploring the consequences, delineating the various outcomes associated with the implementation of data governance.

FIGURE 8. The DAMA wheel [1].

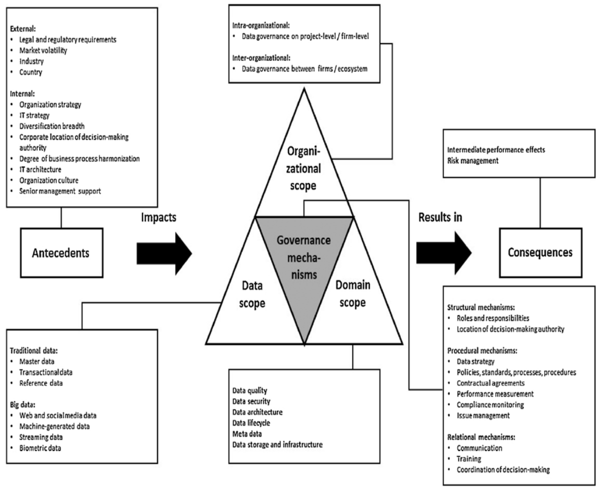

FIGURE 9. Sample of Conceptual framework for data governance [16].

Data governance mechanisms are the tools, processes, and structures that organizations use to manage their data assets effectively, ensuring data integrity, usability, and compliance with regulations. As outlined by DAMA (Data Management Association International) [1], these mechanisms are aligned with the principles in the Data Management Body of Knowledge (DMBOK), providing a comprehensive framework for data governance. The mechanisms are categorized into three types: structural, procedural, and relational. Structural mechanisms refer to the organizational roles, responsibilities, and structures in place to govern data; procedural mechanisms involve the policies, standards, and processes for managing data; and relational mechanisms focus on fostering collaboration and communication among different stakeholders to ensure cohesive data management [16].

The significance of data governance mechanisms lies in their ability to establish clear guidelines for managing and protecting data. They help mitigate risks such as data misuse and unauthorized access and ensure that data practices comply with legal and regulatory requirements [24]. Data stewardship, a key mechanism, involves assigning specific individuals or teams' responsibility for managing data assets, promoting accountability and data quality [9]. By implementing these mechanisms, organizations could decision-making and enhanced competitiveness [30].

We will delve deeper into what the literature reveals about the data governance mechanisms presented in Figure 8. This figure clearly synthesizes the most relevant concepts highlighted in this Systematic Literature Review (SLR). The author, who is the second most cited in Table 11 with 678 citations, and many other studies, also reference this figure 8. These mechanisms are frequently cited by authors as the foundation for the effective management of an organization's data governance assets.

1) STRUCTURAL MECHANISMS

In DG refers to the organizational frameworks, roles, and policies that support the management and use of data across an organization. These mechanisms are foundational elements that define how data governance is structured within a business, ensuring that data is managed effectively, accurately, and in alignment with the organization's goals and regulatory requirements [16].

The organizational structure of DG plays a pivotal role in its effectiveness. A Data Governance Council, composed of senior representatives from different business sectors, sets policies and ensures alignment with business strategies. These councils determine the scope and approach for governing data within the organization. Additionally, clear roles and responsibilities, such as Business Data Stewards and Technical Data Stewards, are critical for ensuring data accuracy, security, and proper usage. These roles play a significant part in managing data compliance and supporting data-driven decision-making. The role of data governance is increasingly becoming central to organizational success as the digital landscape evolves. By integrating robust frameworks, maintaining compliance, and leveraging new technologies, businesses can protect their data assets and drive innovation [10], [28] and [31].

2) PROCEDURAL MECHANISMS

In DG refer to the structured processes, rules, and policies that organizations implement to manage and safeguard their data assets. These mechanisms establish clear procedures for data classification, access control, retention, and deletion, ensuring that data is handled consistently and securely throughout its lifecycle [16]. Procedural mechanisms facilitate collaboration, discussions, and negotiations between stakeholders, encouraging transparency and inclusiveness in decision-making processes. They serve as a foundation for efficient and effective data management across organizational operations, supporting data integrity, security, and regulatory compliance [9] and [12].

The first step in procedural governance involves establishing data classification and categorization systems, which are foundational for securing and managing data. These systems help protect sensitive information and ensure compliance with governmental standards. Identity management systems (IMS) and data access controls are also key procedural mechanisms, ensuring users only have access to the data necessary for their roles [32], [33]. This protects data integrity and minimizes risks associated with unauthorized access. Additionally, robust data retention and deletion policies play a critical role in procedural governance by reducing unnecessary data storage and demonstrating a commitment to privacy and legal obligations. Effective data retention practices support both operational efficiency and compliance with ethical and legal standards [4], [34]. Another crucial aspect of procedural mechanisms is the establishment of governance roles, such as Chief Data Officers and Data Stewards, who oversee the implementation of governance policies and ensure their adherence across the organization [31]. These roles help maintain accountability and guide organizations toward meeting their data governance objectives [35]. Training programs are essential to ensure that employees understand relevant laws and regulations, and monitoring and evaluation processes are necessary to assess the effectiveness of governance frameworks [36]. Together, these procedural mechanisms create a structured system for managing data and ensuring compliance within an organization [28].

3) RELATIONAL MECHANISMS

in data governance refer to the interactions, collaboration, and trust-building between individuals and teams within an organization that facilitate effective data management. These mechanisms are crucial for fostering cooperation among stakeholders, creating a shared understanding of data governance principles, and ensuring that data governance policies are followed consistently across the organization. Unlike formal procedural or structural mechanisms, relational mechanisms focus on human interactions and the role of trust, feedback, and collaboration in ensuring the smooth operation of governance frameworks. They contribute to building cohesive teams and strengthening relationships that underpin data governance efforts [14], [16].

In a data governance setting, relational mechanisms emphasize cooperation, communication, and the establishment of trust-based relationships between stakeholders. These mechanisms not only support formal governance processes but also enhance them by facilitating continuous coordination and interaction. Relational mechanisms help clarify complex interdependencies within organizations and enable collective action on issues such as data quality and security [37]. For example, trust-seeking and bonding mechanisms allow teams to collaborate more effectively by creating personal or social bonds, which are vital for long-term success in governance projects. Additionally, reciprocity mechanisms encourage disciplined actions in data handling by fostering mutually beneficial interactions between data stakeholders [30].

By complementing formal instruments such as policies and enforcement measures, relational mechanisms enhance the overall effectiveness of data governance. These mechanisms are particularly important in ensuring that informal and formal governance tools work in harmony, leading to better organizational performance [35]. As relational mechanisms help build shared practices and foster collaborative environments, they become a critical part of measuring the success of data governance efforts. Future research in this area should focus on developing empirical strategies to assess the effectiveness of relational mechanisms in business settings, as understanding their impact remains a relatively unexplored but essential aspect of data governance [25], [38].

Data Governance Scope refers to the extent of governance activities required to manage and utilize an organization's data assets effectively. It defines the boundaries within which data management policies, procedures, and responsibilities operate, ensuring that data quality, security, compliance, and proper utilization are maintained throughout the organization. A clear scope helps prioritize data governance efforts, align them with business objectives, and allocate resources effectively. By setting these parameters, organizations ensure that data governance is tailored to specific needs and challenges [2], [11], [37]. We will explore in detail *the data governance scopes* demonstrated in Figure 8.

4) DATA SCOPE

Data governance involves the practices and technologies used to create formal registries of data attributes, such as Master Data Management (MDM), data quality, and data modeling. One of the key steps in this process is defining the data scope, which determines which data will be governed. While there is no consensus in the literature regarding the terminology or methodology for defining the scope, it is generally agreed that the scope should be aligned with the organization's operational, tactical, and strategic goals. However, a standardized guide for determining this scope is often missing. The scope's definition plays a critical role in aligning IT and business objectives and ensuring data governance initiatives are comprehensive [16]. Data governance can be applied both within an organization (intra-organizational) and between organizations (inter-organizational), expanding its complexity and importance depending on the scale of collaboration and data sharing [35].

In intra-organizational data governance, the focus is on managing data within a single entity, ensuring data quality and integrity across departments, aligning data strategies with business goals, and ensuring compliance with internal policies. The clear definition of roles, such as data stewards, helps maintain governance structures that prioritize data accuracy and secure access to sensitive information [39]. On the other hand, inter-organizational data governance expands beyond a single entity to include external stakeholders such as suppliers, partners, and regulatory bodies. This broader governance scope requires mechanisms like standardized data-sharing protocols and service-level agreements (SLAs) to ensure secure collaboration between organizations while balancing risks and rewards associated with data handling [9], [40].

Establishing the data scope also includes policies that control access to high-quality data, the definition of data items, and the stakeholders or domains to be governed. These policies should be applied across different data types, whether data is stored, in transit, or externally sourced. Data scope plays an essential role in classifying data as an asset and ensuring that organizations treat their data accordingly. By properly defining and managing data scope, organizations can ensure that they fulfill stakeholder requirements, optimize business processes, and extract maximum value from their data [11]. This process also involves implementing a metadata catalog to increase data visibility and value, making data more understandable and accessible across the organization, whether it is used internally or shared externally through inter-organizational efforts [25].

In conclusion, data governance frameworks must incorporate well-defined data scopes to enhance data management practices. These scopes involve a wide range of elements, such as data quality, data lineage, and data distribution, and must be tailored to the specific industry or organizational context. By doing so, organizations -whether operating within a single entity or collaborating across multiple organizations - can ensure alignment between their data management goals and operational processes, leading to improved business outcomes and regulatory compliance [38].

5) DOMAIN SCOPE

Defining the domain scope is a crucial first step in any data governance initiative. A domain in data governance is typically defined as the unit of data that will be managed and governed by the system. Domains encompass data and various related artifacts and are managed under consistent policies, ensuring data integrity, security, and governance operations. Organizations may define domains based on specific business units, data sources, or functional areas, ensuring that data management is aligned with the overall goals of the organization [37]. Different organizations may classify domains based on various attributes, such as purpose, security, or application, depending on their unique needs. In this context, domain scope is integral to ensuring that data policies are applied uniformly across all relevant areas, improving the consistency and reliability of data management practices [19].

Furthermore, domain scope plays a critical role in structuring data governance programs, especially in the classification of data decision domains. Key areas such as data quality, security, architecture, lifecycle, metadata, and storage are often considered when defining the scope of a data governance initiative [6]. Broadening the domain scope can enhance governance efforts, but it may also require tradeoffs, particularly when balancing regulatory compliance with operational efficiency. Organizations must also consider geographical scope and the alignment of data governance services across different regions and business functions to ensure a cohesive governance strategy [12]. By focusing on the domain scope, organizations can better manage the complexities of data governance and ensure that all data governance efforts are aligned with business needs and regulatory requirements [9].

Additionally, a comprehensive domain scope facilitates the alignment of data governance with strategic business objectives by ensuring that the framework addresses specific operational needs. It supports the integration of governance policies across various data domains, ensuring that all aspects of data, from creation to deletion, are managed according to consistent standards [11]. This includes developing detailed data stewardship roles, establishing data ownership, and applying policies related to data privacy, security, and compliance [30]. Moreover, domain scope enables organizations to define how data will be shared and accessed within and between departments, providing the necessary structure for both intra-organizational and inter-organizational collaboration [39]. It also allows for agility in adapting to evolving regulatory requirements and the changing data landscape [41].

In conclusion, a well-defined domain scope is critical to the success of data governance initiatives. It ensures that data governance efforts are aligned with organizational objectives, supports the management of data across different units or regions, and facilitates compliance with regulatory standards. By focusing on the right domain scope, organizations can enhance their data management practices, improve data quality and security, and optimize the value they derive from their data assets. Ultimately, a clear and comprehensive domain scope sets the foundation for effective and sustainable data governance [8] and [42].

In the context of Data Governance, antecedents are often referred to as the drivers, motivators, or factors that lead organizations to implement data governance frameworks. These could include regulatory requirements, business objectives, technological advancements, or the need to mitigate risks associated with data breaches and poor data quality. For instance, regulatory compliance is a critical driver, particularly as more stringent data protection laws such as the GDPR have emerged [11]. Similarly, the increasing complexity and volume of data, along with the demand for high-quality, reliable data for decision-making, are also key motivators [16]. Essentially, antecedents are the reasons or triggers that prompt an organization to adopt structured data governance practices [19].

On the other hand, consequences are typically referred to as the outcomes, results, or impacts of implementing data governance. These may include improved data quality, enhanced regulatory compliance, better decision-making, operational efficiency, or an overall more data-driven culture within the organization [12]. For example, organizations that have implemented strong data governance frameworks report significant improvements in data consistency, compliance, and operational efficiency [7]. In addition, effective data governance can mitigate risks related to data privacy and security, ultimately safeguarding sensitive information and promoting trust among stakeholders [39]. These outcomes reflect the tangible benefits and changes that occur because of proper data governance implementation as detailed next.

6) ANTECEDENTS

As mentioned in data governance context, external and internal factors significantly influence its adoption and implementation. Despite increased investments in data management, challenges such as delays in information consumption, complexity in managing diverse data types, and the use of multi-cloud strategies can hinder the progress of large-scale data governance initiatives [34].

External antecedents refer to factors outside the organization that influence the adoption of data governance practices. These include technological advancements like big data analytics, changes in legal regulations such as consumer data privacy laws, and evolving market demands [43]. Organizations need to be agile in adapting to these external forces to ensure their data governance strategies remain relevant and effective. However, challenges such as the complexity of managing diverse data types, multi-cloud environments, and delays in information sharing can hinder successful implementation [44].

Internal antecedents, on the other hand, are factors within the organization that affect data governance. These include domain-specific factors like business and data literacy, strong leadership, and vision [45]. Organization-specific elements focus on engagement, commitment, and readiness to address data-related challenges, while personnel-specific factors emphasize valuing data, continuous education, and fostering a data-driven culture [36]. Despite the potential, challenges such as low internal data literacy, insufficient leadership support, and underdeveloped data governance frameworks continue to slow progress in this area [37]. Addressing both external and internal antecedents is crucial to overcoming these barriers and implementing effective data governance strategies.

7) CONSEQUENCES

Data governance is a multi-level field that helps organizations manage data complexities and align them with business objectives. A comprehensive data governance model assists managers in understanding how their actions impact data across the organization. This framework not only supports decision-making but also plays a critical role in achieving higher levels of governance maturity by ensuring data management practices are structured and effective [30].

One of the critical aspects of data governance is the understanding of control, evaluation, and consequences. These elements define how governance actions affect the organization's ability to manage data-related risks, such as data breaches, compliance failures, and quality issues. Recognizing the consequences of governance decisions allows organizations to proactively mitigate risks and implement remedial measures, ensuring smoother project execution. Proper governance also boosts performance, with higher data quality leading to better decision-making, efficiency, and customer satisfaction [46].

Consequences play a vital role in the maturity level of data governance. As organizations advance in their governance practices, they begin to understand and anticipate the outcomes of their data management decisions. Mature data governance includes mechanisms for measuring the impact of governance policies, such as improved data accuracy, enhanced security, and regulatory compliance. By focusing on the consequences, companies can assess the effectiveness of their governance strategies and make data-driven improvements that contribute to continuous growth [47].

Measuring the consequences of data governance initiatives is essential for tracking progress and ensuring that governance practices are delivering the desired outcomes. Organizations that regularly evaluate the effects of their governance decisions can make informed adjustments, ultimately enhancing their governance maturity. By doing so, they can ensure that their data governance framework not only supports current business needs but also evolves with future challenges and opportunities [44], [48].

8) MATURITY LEVEL

In the context of data governance, assessing maturity is essential to understand how well an organization manages its data assets and aligns governance practices with strategic goals. Throughout the literature, several maturity models have been proposed to support this evaluation. This Systematic Literature Review (SLR) highlights six models of relevance: DGM2 [44], DGCMM [49], CMMI [29], and Stanford Data Governance Model [27]. While all offer valuable contributions, the CMMI and DGCMM models were explored in greater depth due to their wide applicability, frequent use in empirical studies, and strong alignment with the research objectives. CMMI is widely known for its structured maturity levels and focus on continuous process improvement, making it suitable for evaluating data governance practices across various organizational settings [29]. In contrast, DGCMM emphasizes organizational capability and the strategic treatment of data, offering a more tailored approach to diagnosing and enhancing data governance effectiveness [49].

The decision to concentrate on these two models is also supported by their ability to clearly define maturity levels and evaluation criteria, which are essential for analyzing the impact of structured frameworks on governance maturity. Other models, such as DGM2 [44] and Stanford [27], were acknowledged but proved to be less adaptable to IT governance contexts when compared to CMMI and DGCMM.

Therefore, CMMI and DGCMM were identified as offering the best combination of theoretical foundation, academic relevance, and practical utility in advancing the understanding and implementation of data governance maturity.

In the studies analyzed during the exploration, some maturity models were mentioned and proved to be relevant in this SLR such as the Data Governance Capability Maturity Model (DGCMM) is structured as a process-oriented framework designed to evaluate an organization's ability to manage data as a core asset. The model is used to assess how well data governance practices are implemented and how these practices evolve over time. Typically, organizations move through multiple maturity levels, each representing an increased sophistication in managing data governance tasks. The DGCMM allows organizations to identify gaps in their data governance strategies and implement improvements for better management of data quality, security, and usage efficiency [29].

Maturity impacts data governance by providing a structured approach to advancing data management capabilities. As organizations progress through the levels of maturity, they move from ad-hoc and inconsistent practices to more standardized and optimized governance structures. This advancement is critical as it ensures that data is managed in line with organizational goals, regulatory requirements, and evolving technological landscapes. Organizations at higher maturity levels benefit from improved data quality, regulatory compliance, and more effective decision-making processes [33].

Another model cited is the Capability Maturity Model Integration (CMMI) that is by far the most widely used and mentioned maturity model and constantly addressed to assess data governance maturity is appropriate because it offers a well-established method for process improvement across various domains, including data governance and this is the model to be used as reference but not limited to. CMMI's structured approach to evaluating process capabilities helps organizations identify key areas for improvement, making it suitable for managing complex data environments. Its focus on continuous improvement aligns with the evolving needs of data governance, ensuring that organizations can adapt to changing data landscapes while maintaining control and compliance [49].

This combination of DGCMM and CMMI methodologies offers organizations a comprehensive toolset to manage, measure, and continuously improve their data governance practices, contributing to better data-driven outcomes [42].

All the details and comparison between them can be seen in Figures 10 to 13.

Framework	DGCMM (Data Governance Capability Maturity Model)	CMMI (Capability Maturity Model Integration)
Origin	Developed for **assessing and improving** data governance within organizations	Created by **Software Engineering Institute (SEI)** for **process maturity improvements**
Focus	**Capability-based assessment** of an organization's **data governance maturity**	**Process maturity framework** designed to optimize **business and IT processes**
Objective	Establish a **structured approach** to data governance maturity assessment and enhancement	Provide a **structured methodology** for improving **processes, efficiency, and compliance**

FIGURE 10. Maturity models overview.

IV. LANDSCAPE: FUTURE RESEARCH PATHWAY

The preceding discussion establishes a theoretical structure for data governance, encapsulating a thorough synthesis of studies and key discoveries pertinent to the field thus far. Stemming from specific elements highlighted in our prior analysis, it was proposed to have a research roadmap in the realm of data governance. This future research pathway is delineated into six key dimensions: (I) governance mechanisms; (II) scope of data governance; (III) Antecedents to data governance; (IV) Consequences of data governance; (V) the ability to generalize and replicate outcomes; and (VI) Measuring and evaluating the maturity level possible impacts.

Feature	DGCMM	CMMI
Structure	Focused exclusively on data governance	Covers broader business processes and IT governance
Governance Maturity Focus	Evaluates data governance readiness and capabilities	Measures organizational process maturity
Scalability	Adaptable to various business sectors	Suitable for small, medium, and large enterprises
Process Improvement	Focuses on governance mechanisms, data quality, and compliance	Covers a wide range of business process improvements
Implementation Complexity	Moderate, but requires data governance expertise	High, due to its comprehensive and formalized process approach
Compliance & Security	Assesses compliance with governance best practices	Used for regulatory compliance, risk management, and security enhancements
Measurement Approach	Uses governance capability metrics	Uses process maturity levels (1 to 5)

FIGURE 11. Maturity models key features comparison.

	DGCMM	CMMI
✅ Pros	✅ Focused on data governance improvements	✅ Comprehensive framework for process optimization
	✅ Provides structured assessment criteria	✅ Well-established and widely adopted across industries
	✅ Can be applied to different sectors	✅ Strong compliance and risk management approach
❌ Cons	❌ Requires specialized knowledge of data governance principles	❌ High complexity and long implementation time
	❌ Not as well-known as CMMI	❌ Can be bureaucratic and rigid in certain environments

FIGURE 12. Maturity models Pros & Cons.

Context	Best Option
Organizations looking to evaluate and improve data governance maturity	✅ DGCMM
Enterprises seeking process maturity improvements across various domains	✅ CMMI

FIGURE 13. Maturity models best choice by context.

To further support the ongoing advancement of data governance, it is critical to foster interdisciplinary collaboration. By integrating insights from fields such as information technology, business management, and compliance, researchers can develop more robust governance frameworks. These frameworks should not only address current regulatory and technological challenges but also anticipate future trends and disruptions.

In conclusion, our analysis not only underscores the importance of a structured approach to data governance but also highlights the necessity for continuous evolution in research methodologies. As new technologies emerge and data landscapes become more complex, updating and adapting our research agenda will be crucial. This will ensure that data governance frameworks remain effective and relevant, thereby enhancing organizational performance and compliance in an increasingly data-driven world.

A. DATA GOVERNANCE MECHANISMS PATHWAY

In today's data-driven environment, data governance mechanisms play a vital role in managing and safeguarding data, which is now viewed as one of an organization's most crucial assets. High-profile data breaches have increased awareness among executives of the risks associated with poor data governance, highlighting the need for strong mechanisms. Despite the growing importance of data governance, organizations face challenges in balancing stakeholder needs and implementing effective governance tools. Advanced technologies like machine learning (ML) and artificial intelligence (AI) require precise data management to avoid biased or erroneous outputs. The rise of the Internet of Things (IoT) further complicates governance, given the large volumes of real-time data that fuel these models.

Data governance ensures that organizational data is effectively managed through clearly defined ownership, accountability, and policies. Despite these frameworks, increasing security breaches and data-related lawsuits underscore the need for comprehensive governance mechanisms. Regulatory-driven programs often focus on specific data elements, whereas analytics-driven initiatives may govern broader data domains. Research is needed to better understand how the scope of data ownership impacts governance success and how decision-making structures can be optimized.

The literature also emphasizes the evolving nature of data governance, as it must adapt to both internal organizational needs and external pressures, such as regulatory changes. Governance is increasingly seen as a dynamic, rather than static, process, calling for ongoing qualitative, quantitative, and longitudinal studies to ensure that it remains effective in the face of shifting technological and regulatory landscapes [29], [46], [47].

Integrating AI and ML into data governance frameworks is reshaping organizational strategies. AI-driven tools significantly enhance data quality by detecting patterns and anomalies in real time, enabling faster and more accurate decision-making. Moreover, ML simplifies compliance by automating tasks and ensuring adherence to regulations, thus reducing associated costs and risks [24], [50].

The *ability of Real-Time Data Governance* to make data-driven decisions instantly is a key differentiator. Real-time data governance allows organizations to continuously process and analyze data, generating valuable insights that support immediate actions. Since AI and ML models thrive on fresh data, adopting dynamic governance strategies ensures these technologies operate using the most current and relevant information [38], [50].

Choosing between *centralized and decentralized data governance models*is a strategic decision that affects how policies are implemented and enforced. Centralized models offer consistency and control, whereas decentralized frameworks—such as data mesh—provide flexibility, allowing individual teams to tailor data management to their specific needs. A hybrid model may combine the strengths of both approaches, fostering both innovation and compliance [26], [43].

Incorporating *ethical principles into AI* ensures responsible use of data, promoting transparency and alignment with societal values. Ethical data governance is essential for maintaining public trust and ensuring that governance practices respect individual and collective rights [17], [43].

Cloud technology has revolutionized data governance by offering scalable solutions that support AI and ML initiatives. Cloud-based platforms allow for the storage, management, and processing of large datasets more efficiently, facilitating faster, AI-driven insights. These platforms also provide robust security features, ensuring data integrity and regulatory compliance in a cost-effective manner [11], [24].

Organizations are increasingly focusing on key performance indicators (KPIs) to assess the success of their data governance strategies. Data quality metrics, cost savings from reduced manual processing, and improved compliance are among the most important *Return on Investment (ROI) indicators*. Tracking these results not only justifies further investment but also helps ensure that AI efforts remain aligned with strategic objectives [19], [45].

To further enhance the effectiveness of data governance mechanisms, future research should explore:

- *Synthetic Data Governance: Investigate the challenges and opportunities presented by synthetic data use, especially regarding bias, security, and data integrity [24], [38].*
- *Data Cooperatives: Examine democratic models of data governance, such as data cooperatives, which enable individuals to collectively control their information, fostering ethical and sustainable practices [17].*
- *Dynamic Consent: Develop approaches that allow individuals to manage their data-sharing preferences in real time, increasing transparency and trust [17].*
- *Governance in Multimodal Data Environments: Explore governance frameworks that integrate diverse data sources to better understand human behavior while ensuring data quality and ethical handling [50].*
- *Data Governance for AI: Analyze how data governance must adapt to meet AI-specific needs, ensuring that the data used is of high quality, secure, and ethically sound [50].*

These research areas are crucial to developing data governance frameworks that are resilient, adaptable, and aligned with emerging technological and societal demands.

B. SCOPES OF DATA GOVERNANCE PATHWAY

The *scopes* span across various disciplines, touching on technological, organizational, and ethical aspects. Its importance is recognized for fostering better governance practices and promoting collaboration among stakeholders, such as policymakers, businesses, and institutions. The need for comprehensive frameworks and roadmaps in data governance is emphasized, aiming to address the complexity of governing data in the age of big data and machine learning.

Despite its potential, data governance research remains fragmented and narrowly focused, often lacking a holistic perspective. The existing literature is highly prescriptive and operational, focusing more on best practices than on conceptual clarity or empirical validation. This has limited the widespread adoption of data governance models within organizations [16], [24] and [50].

Future investigations should prioritize the development of holistic and empirically grounded frameworks that integrate technological, organizational, ethical, and legal dimensions. Abraham et al. [16] emphasizes the need for unified theoretical foundations capable of addressing the multifaceted challenges posed by modern data environments. This includes designing adaptable models that cater to a broad range of industries and governance contexts.

Another critical direction involves aligning data governance practices with societal values such as fairness, transparency, and accountability. As highlighted by Janssen et al. [50], governance mechanisms must extend beyond regulatory compliance to ensure ethical oversight, especially in contexts involving AI and automated decision-making. This requires rethinking how ethical principles can be effectively embedded into governance policies and operational procedures.

Additionally, longitudinal research is needed to understand how organizations mature in their governance capabilities over time. Houser and Bagby [24] advocate for adaptive models that reflect the ongoing evolution of technologies and organizational needs. Such models should serve not only as assessment tools but also as strategic instruments for guiding continuous improvement in governance practices.

Comparative analyses of data governance frameworks across different sectors and regions also offer promising insights. Benchmarking initiatives, like the one conducted by Marcucci et al. [25], provide valuable evidence on which models are most effective in specific contexts, and how lessons learned in one domain can inform practices in others. These studies support the development of governance approaches that are both context-sensitive and globally informed.

Finally, the rapid adoption of emerging technologies such as data mesh, blockchain, and edge computing calls for a reexamination of governance paradigms. As shown by Wider et al. [26], decentralized models introduce new possibilities and complexities, demanding empirical research to assess their practical viability and implications for accountability, control, and data quality.

C. ANTECEDENTS AND CONSEQUENCES PATHWAY

Understanding the antecedents of data governance is becoming increasingly critical, as organizations face mounting regulatory pressures, risk exposure, and growing recognition of data as a core strategic asset. Key factors that trigger the adoption of governance frameworks include regulatory obligations, organizational maturity, market expectations, and industry-specific compliance needs. However, as highlighted by Abraham et al. [16], research in this area often lacks theoretical depth and empirical consistency, making it difficult to generalize or tailor governance strategies across sectors. Future research should focus on systematically identifying and categorizing these antecedents through comparative and longitudinal studies that consider different organizational contexts and industry characteristics.

One pressing research avenue involves deepening the understanding of how foundational data governance capabilities such as metadata management, data quality, and lineage act as enablers of successful implementation. These core components are widely acknowledged in practice but often underexplored in academic literature. As noted by Legner et al. [18], there is a need to connect these technical dimensions with organizational strategy, ensuring that they are not treated in isolation. Research should examine how the integration of these elements within governance models can drive greater adoption and effectiveness across varying organizational structures.

When considering the consequences of data governance, the scope extends far beyond regulatory compliance and risk mitigation. Well-structured governance can drive transformation by enabling data-driven innovation, especially in customer engagement, digital services, and platform-based business models. However, as Janssen et al. [50] point out, evaluating these outcomes is complex and multidimensional. Future studies should employ mixed-methods research designs to explore how data governance contributes to value creation, improved decision-making, and cost optimization—while accounting for moderating variables such as organizational culture, technological infrastructure, and external institutional factors.

Another promising line of inquiry involves examining how governance frameworks influence organizational behavior, leadership, and decision rights. As highlighted by Micheli et al. [47], governance is not merely a technical or bureaucratic function; it reflects and shapes power relations, accountability mechanisms, and strategic direction. Investigating how data governance impacts managerial decision-making, team autonomy, and strategic agility can offer insights into its transformative role. Future work should also explore the governance-innovation nexus, particularly how clarity in data stewardship fosters or constrains experimentation and agility in data-intensive initiatives.

Furthermore, the adoption of data governance affects internal governance models and has implications for cross-functional coordination, platform ownership, and ethical stewardship of data. These dynamics underscore the need to approach governance as both a technical architecture and a social system. Researchers should explore how governance interacts with organizational identity, trust in data, and inter-departmental collaboration. Such analysis would benefit from case studies and ethnographic research in diverse sectors, providing contextual depth to the study of governance consequences [16].

Lastly, substantial research gaps remain regarding the systemic outcomes of governance strategies across industries and regulatory environments. Although existing frameworks provide conceptual guidance, their operationalization is often unclear or inconsistent. As Abraham et al. [16], Micheli et al. [47], and Janssen et al. [50] collectively suggest, future research must move toward the empirical validation of governance models and their real-world impact. This includes exploring how governance strategies can be better aligned with stakeholder expectations, business models, and evolving societal demands ensuring that governance practices are not only effective but also contextually relevant and sustainable.

D. DG MATURITY MODEL PATHWAY

The development and implementation of data governance maturity models have become essential for organizations aiming to manage data as a strategic asset. These models serve not only as diagnostic tools but also as roadmaps for aligning governance structures with business objectives. At their core, maturity models help organizations understand their current stage of data governance and identify pathways for evolution, integrating aspects such as data quality management, governance structures, and organizational culture. As highlighted by Mahanti [42], a robust maturity model must connect data quality initiatives with strategic management principles, ensuring that improvements in data accuracy and reliability are directly tied to organizational performance.

A key area of inquiry involves deepening the relationship between data governance and performance indicators, particularly in terms of innovation, process efficiency, and competitive advantage. Organizations that operate within complex ecosystems engaging with regulatory bodies, suppliers, and partners require mature governance capabilities to support standardized, high-quality data exchanges. As noted by Saputra et al. [44], the ability to maintain consistent data definitions and practices across departments and stakeholders is a strong indicator of governance maturity. Future research should examine how such maturity affects inter-organizational collaboration and digital transformation outcomes in various sectors.

The use of Key Performance Indicators (KPIs) is central to assessing the effectiveness and progression of data governance initiatives. KPIs related to data accuracy, timeliness, completeness, and consistency offer quantitative insights into the success of governance programs. Kurniawan et al. [29] emphasize that these metrics must be context-aware and strategically aligned, guiding both operational improvements and executive decision-making. However, existing maturity models often lack detailed guidance on selecting and adapting KPIs to different organizational environments. Further empirical research is needed to establish standardized, yet flexible KPI frameworks that accommodate sector-specific requirements.

Scoring methodologies embedded in maturity models also warrant closer examination. While these tools offer structured ways to evaluate progress, they risk becoming overly rigid or biased if not properly calibrated. Mahanti [42] warns that poorly designed scoring systems can hinder rather than support governance evolution. Future investigations should focus on refining scoring mechanisms to ensure objectivity, comparability, and relevance, possibly incorporating AI-based assessment tools or benchmarking databases for dynamic evaluation.

Another significant research opportunity lies in studying the longitudinal application of maturity models. While many organizations use these models as one-time diagnostic tools, there is limited understanding of how maturity evolves over time and what factors influence sustained governance improvements. Studies should adopt longitudinal case study methods to track the lifecycle of data governance programs, identifying the enablers and barriers that affect progression through maturity stages. Such research could inform the design of adaptive models that evolve in response to organizational change, technological advancement, and regulatory shifts [44].

Finally, the integration of maturity models with broader strategic management frameworks—such as the balanced scorecard—presents a valuable direction for inquiry. This integration can offer a holistic view of how data governance contributes to financial performance, customer satisfaction, internal processes, and learning and growth. Empirical research is needed to test how combined frameworks function in practice and whether they produce superior outcomes compared to standalone data governance assessments [42].

In conclusion, while maturity models have become foundational in the governance landscape, their refinement and contextual adaptation remain open areas of research. Building on the contributions of Mahanti [42], Saputra et al. [44], and Kurniawan et al. [29], future studies must address gaps in scoring logic, KPI integration, strategic alignment, and longitudinal validation. Advancing these models is essential for organizations seeking to govern data not just effectively, but also in ways that are sustainable, strategic, and responsive to change.

V. CONCLUSION

This systematic literature review (SLR) offers a comprehensive insight into the domain of data governance, aiming to bridge the gap between academic research and practical implementation. The study meticulously reviewed over a hundred publications from the past decade, focusing on six critical dimensions of data governance: governance mechanisms, organizational scope, data scope, domain scope, antecedents, and consequences.

Significance and Impact: The findings underscore the increasing importance of structured data governance approaches in enhancing organizational performance and ensuring compliance with regulatory requirements. With the exponential growth of data and the advent of stringent regulatory frameworks, the role of data governance has become paramount in modern business practices.

Frameworks and Mechanisms: The study highlighted the importance of adaptive frameworks and mechanisms in data governance. These include structural, procedural, and relational mechanisms that interact with governance to enhance data management practices within organizations.

Measuring and Maturity Levels: The research emphasized the importance of measuring data governance maturity levels to identify areas for improvement and track progress. The concept of maturity levels helps organizations understand their current state and set targets for future development. However, the study noted that defining and assessing maturity remains under-researched and under-theorized. Establishing a scoring methodology to measure the maturity of the Data Governance Framework is crucial, as it provides insight into the data governance maturity and helps set priorities for improvement actions. Common approaches for assessing maturity levels, such as the Software Engineering Institute's model, are vital in the initial phase but often require adaptation to fit the specific context of data governance.

Limitations and Future Research: The review identified several gaps in the current understanding of data governance and proposed a future research agenda enriched with critical inquiries for subsequent investigation. It emphasizes the need for expanding research methodologies to include a broader and more diverse sample of organizations and stakeholders beyond IT and data management executives. Additionally, the integration of quantitative approaches and longitudinal analyses could provide deeper insights into the causal relationships between governance frameworks, maturity progression, and organizational outcomes.

Future studies should also explore cross-sectoral comparisons, particularly examining how governance frameworks perform in industries with distinct regulatory and technological contexts. By incorporating multidisciplinary perspectives, future research can develop more adaptive and resilient models capable of addressing both emerging data governance challenges and the evolving landscape of digital transformation.

Furthermore, the doctoral research that follows will move beyond theoretical synthesis to empirically validate the proposed conceptual framework within real organizational environments. This validation phase will employ a mixed method design combining case studies, expert evaluations, and maturity assessments to test the framework's applicability, reliability, and impact on data governance performance. By doing so, the doctoral work will transform the conceptual model derived from this SLR into an operational, evidence-based construct, thereby ensuring methodological continuity and reinforcing the contribution of this study to both academic and practical domains.

This SLR represents a significant advancement over previously established studies, such as those by Abraham et al. [16] and Nielsen [14], by adopting a more applied, comprehensive, and maturity-oriented approach to data governance. While Abraham et al. propose a conceptual framework based on theoretical dimensions and Nielsen highlights methodological fragmentation and the lack of an integrated organizational perspective, this SLR consolidates and expands these contributions by structuring its systematic literature review around governance mechanisms (structural, procedural, relational), multiple scopes (organizational, data, and domain), and a comparative analysis of maturity models, such as DGCMM and CMMI. The study's key differential lies in its practical orientation: it presents evaluation criteria, performance indicators (KPIs), and an analysis of the antecedents and consequences of adopting governance frameworks, offering a clear methodological path for application and assessment in organizational environments. As such, this SLR marks an important progression by transforming existing theory into operational guidelines and a foundation for developing replicable, maturity-driven data governance models.

In conclusion, this SLR synthesizes current knowledge in the field of data governance, charting a path forward for both academic and corporate exploration. By fostering a holistic understanding of the effectiveness, challenges, and limitations of data governance, this study lays a foundational step towards realizing the full potential of data governance, providing all the knowledge and tools needed for the development of next steps.

The next steps involve the development of a doctoral thesis focused on proposing a master data management framework aimed at triggering data governance maturity, supported by research and a case study to evaluate its effectiveness. This SLR will serve as a foundational reference, guiding the research by identifying relevant maturity models, frameworks, and key concepts that will shape the proposed framework and its implementation. It will provide a structured basis for selecting the most suitable governance methodologies and approaches, ensuring a well-grounded and methodologically sound exploration of data governance maturity.

Data governance policies and standards are vital for defining the roles, responsibilities, and processes that govern data use. These policies help in creating a culture of accountability and ensuring that the organization's data assets are used effectively and responsibly.

For example, compliance monitoring within data governance frameworks plays a critical role in risk management by ensuring that all data practices adhere to legal and regulatory standards. These practices include regular audits, reviews, and updates to governance policies as regulatory and business environments evolve.

The landscape of data governance continues to evolve as technology advances and regulatory environments become more complex. Organizations must adapt their data governance frameworks to accommodate emerging technologies such as artificial intelligence and machine learning, which pose new challenges and opportunities for data management.

The integration of comprehensive data governance frameworks into organizational strategy is crucial for building a resilient foundation for data management. As organizations continue to recognize the strategic value of data, the role of data governance as a critical function will expand, further embedding its principles into the fabric of organizational processes and culture [16].

Data governance frameworks significantly contribute to improving the maturity levels of data assets and user competencies within an organization. Maturity in data governance refers to the extent to which data management practices are formalized and integrated into the daily operations and strategic planning of an organization. Higher maturity levels indicate more sophisticated, predictable, and effective data management practices.

For instance, [27] emphasized that assessing the maturity level of data governance functions is crucial for identifying gaps and planning improvements. By leveraging frameworks such as the Stanford Data Governance Model, organizations can systematically enhance their governance practices, thus achieving higher maturity levels.

The adoption of data governance within organizations is driven by several antecedents, including the need for enhanced data quality, security demands, regulatory compliance, and the strategic use of data for business innovation [28]. These antecedents set the stage for a comprehensive approach to managing an organization's data assets effectively.

The impacts of implementing data governance are profound, ranging from improved decision-making and operational efficiencies to enhanced compliance and risk management. Data governance provides a structured framework to capitalize data as a strategic asset, thereby supporting business objectives and driving innovation.

The scope of data governance extends across the entire organization, influencing various departments from IT to marketing, finance, and operations. It encompasses all aspects of data management, including data quality, data access, data lifecycle management, and data security.

Consequently, the successful implementation of data governance leads to several positive outcomes for organizations. It enhances the maturity level of data management practices, making them more systematic and mature. This transformation supports better compliance with data protection regulations and improves the overall reliability and value of data assets. Organizations become more agile, with the ability to respond quickly to market changes and opportunities, thereby gaining a competitive edge [28].

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