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A FRAMEWORK TO ENHANCE DATA QUALITY IN MASTER DATA MANAGEMENT PROCESS: A HEALTHCARE STUDY

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ABSTRACT

For modern enterprises, to guarantee the quality and accuracy of their fundamental business data, master data management (MDM) is essential. However, a lack of connectivity between data governance and data quality throughout deployment is the reason why many MDM programs fail. This paper introduces a six-phase MDM framework that specifically integrates stakeholder-driven governance and data quality dimensions into each phase of the MDM lifecycle. Based on the PRAXEME methodology and designed using Business Process Model and Notation (BPMN), the framework emphasizes real-time monitoring and facilitates departmental collaboration. A healthcare case study illustrates its efficacy in enhancing data comprehensiveness, minimizing redundancy, and boosting operational productivity. The proposed framework offers a comprehensive approach that aligns business and IT objectives and reinforces process transparency.

I. INTRODUCTION

In last years, the volume of organizational data has expanded significantly with the proliferation of advanced technologies such as cloud computing, IoT, and AI-driven applications that capture information in multiple formats. Much of this data is structured and can be classified into four main categories: master data, historical data, transactional data, and metadata. Among these, master data is the highest priority because it contains the critical information that defines and supports the organization's core operations [1, 2]. Master data are the data describing the most relevant business entities, on which the activities of an enterprise are based, e.g. suppliers, customers or products [1]. In contrast to transactional data (invoices, orders, etc.) and inventory data, master data are oriented towards the attributes. They describe the main characteristics of objects in the real world [3]. Single master data entities are rarely being changed and are relatively constant, especially if they are compared with transactional data. Master data acts as the essential basis for transactional data. Without it, no order or delivery can take place.

In modern digital organizations, the rapid expansion of data sources and IT systems makes it increasingly difficult to maintain a single, reliable view of critical business entities, such as customers, products, suppliers, and assets, which often end up duplicated and inconsistently managed across fragmented infrastructures. This data fragmentation harms not only day-to-day operations but also strategic decision-making and customer satisfaction. As a result, Master Data Management (MDM) has become critical to ensure the consistency, governance, and integrity of foundational business data [4].

There are many reasons why a company might consider MDM, which is defined as "the management of the consistent and uniform subset of business entities that describe the core activities of an enterprise" [1]. Using Master Data Management, valuable master data from multiple organizations is identified and consolidated into a central repository. This centralized system acts as a "single source of truth" supporting various applications across different government entities [5]. While several well-known frameworks for Master Data Management (MDM) exist, such as Gartner's Seven Building Blocks of MDM and the DAMA-DMBOK (Data Management Body of Knowledge), they often take a rather top-down and technical perspective. These models tend to concentrate on aspects like system architecture, governance policies, or abstract principles. What they frequently lack is practical, hands-on guidance on how to deal with real-world challenges, such as ensuring data quality in real time, modeling processes across departments, or involving business and IT stakeholders in a meaningful way. This lack of operational integration often results in MDM initiatives that are difficult to sustain or scale.

To bridge these gaps, this study introduces a six-stage MDM framework that emphasizes continuous data quality control and governance into every step of the data lifecycle. The innovation lies in its holistic approach, which combines Business Process Model and Notation (BPMN) with ongoing metrics for data quality, ensuring clear process visualization and active involvement from both business and IT stakeholders. Unlike traditional frameworks that treat quality and governance as peripheral tasks or post-implementation concerns, this methodology embeds them structurally and continuously into the core of MDM operations. To validate the effectiveness of the framework, a case study is conducted within a major healthcare organization, demonstrating its applicability and added value in a complex data environment. The paper is organized as follows. A literature review on MDM is presented in section 2. The research design and framework development is discussed in section 3, while detailed presentation of the methodology's healthcare sector application, illustrated by case study results are presented in section 4. Section 5 explains about results and discussion. Finally, section [6] concludes the paper and suggests future research directions.

II. LITERATURE REVIEW

The dependability of master data is fundamentally supported by data quality. As noted by [7], 80% of businesses recognize that bad data quality adversely affects their financial performance. In an increasingly regulated business environment, creating a single source of truth has become essential for organizations to stay compliant while remaining competitive [2]. Good data quality is not just a requirement for successfully adopting Master Data Management systems, it's also one of the key benefits organizations can gain when MDM is implemented effectively [1]. Master Data Management is essential for organizations seeking a unified and reliable source of key business data. Many MDM initiatives fail, not due to a sudden collapse, but through a gradual breakdown. These failures often result in poor decision-making, wasted resources, missed opportunities, and inconsistent customer experiences driven by conflicting versions of the truth. Research shows that MDM failure is rarely caused by a single factor.

II.1 DATA QUALITY ISSUES AS A PRIMARY CAUSE

Poor data quality, characterized by inaccuracies, inconsistencies, duplicates, and incompleteness, undermines the reliability of master data repositories. As highlighted by [8], data quality is not merely a technical concern but constitutes a core organizational challenge that necessitates a structured and systematic approach to management. Accordingly, addressing data quality challenges requires the implementation of structured training programs and sustained internal communication strategies, which are essential for fostering organizational awareness and adherence to data quality standards across the MDM lifecycle.

Furthermore, [9] underscores the critical role of continuous quality assessments in ensuring the integrity of master data systems and regular deduplication scans in maintaining high data quality over time. Common sources of poor data quality include fragmented data sources, outdated legacy systems, and inconsistent data entry practices across business units [10]. Additionally, [11] observes that inconsistencies in meeting functional requirements within MDM applications significantly contribute to inefficiencies and data duplication.

II.2 INSUFFICIENT DATA GOVERNANCE FRAMEWORKS

Failures in data governance frequently lead to ambiguous data ownership, poorly defined stewardship responsibilities, and insufficient enforcement of data standards and policies [12]. More recent empirical studies, such as [13], confirm that the absence of robust governance remains a primary barrier to MDM success, as it leads to confusion regarding data ownership and accountability.

The lack of integrated governance frameworks contributes to a disconnect between technical and business teams, causing fragmented and inconsistent data management practices that frequently result in MDM project failure [14]. Furthermore, [15] emphasize that during iterative MDM deployments, misalignment between implemented solutions and organizational requirements frequently originates from deficient governance structures, leading to poor adaptation and integration. According to [16], effective data governance strategies necessitate continuous refinement and are best implemented through an incremental approach, beginning with small-scale initiatives and progressively expanding to broader organizational contexts. To ensure successful implementation, organizations must adopt mechanisms that guarantee the quality of their data assets within the context of their specific operational needs [17].

II.3 TECHNICAL COMPLEXITY AND INTEGRATION CHALLENGES

Lepeniotis [18] emphasizes the detrimental impact of poor planning and sequencing in MDM projects, noting that misaligned execution timelines can exacerbate implementation challenges, ultimately, these challenges can lead to significant financial losses and a decline in overall operational efficiency. Furthermore, [19] argue that MDM initiatives are more likely to fail when approached as purely IT-driven efforts without broader organizational engagement. The absence of stakeholder buy-in frequently gives rise to fragmented and informal governance structures, which in turn obstruct the establishment of consistent data quality practices and compromise the long-term success of MDM initiatives.

While many existing MDM frameworks recognize the importance of data quality and governance, they often treat them as secondary considerations, something to handle later rather than building them in from the start. They also tend to overlook the practical realities of implementation, offering little in terms of tools to help teams align, collaborate, and stay on track. This study takes a different approach: it places data quality and governance at the very heart of the MDM process. By weaving them into every stage, supported by clear visual models using BPMN, it offers a hands-on, collaborative, and sustainable way to manage master data effectively.

III. RESEARCH METHOD

In this section, we detail our proposed methodology. In contrast to existing models that treat BPMN and data quality measurement as retrospective activities, the proposed methodology incorporates these elements from the outset of the MDM implementation process, starting early from strategic alignment and continuing through operational monitoring. This study is derived from the PRAXEME methodology, chosen specifically for its strengths in modeling complex enterprise systems through a multi-perspective and semantically rich approach making it particularly well-suited for Master Data Management projects where conceptual clarity and data traceability are critical [20]. The schematic representation of our methodological approach is illustrated in figure 1.

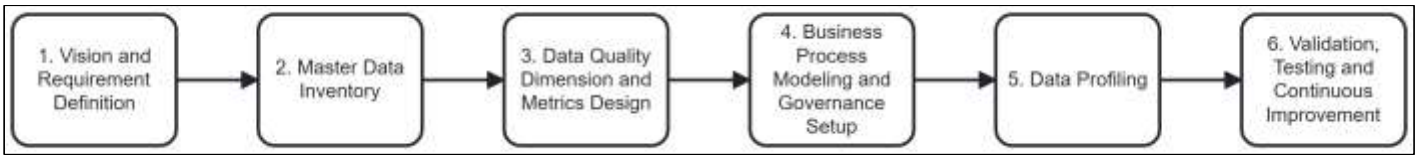

Figure 1: Global methodology.
Source: Authors, (2025).

III.1 VISION AND REQUIREMENT DEFINITION

The success of a Master Data Management initiative begins with a clear vision that aligns business objectives with data governance priorities. Organizations must begin by clearly defining the objectives and anticipated outcomes associated with the implementation of Master Data Management initiatives. During the initial research step, structured and semi-structured interviews with both departmental staff and related units would be conducted to thoroughly analyze the department's operational landscape, uncover critical data challenges, and gather diverse stakeholder perspectives. This process ensures that the MDM framework aligns with actual business needs and operational processes. The interview questions address current data usage, identify existing data issues, and explore expectations for future capabilities. The outcome of this step will be a table that documents the organization’s vision, objectives, and key questions.

III.2 MASTER DATA INVENTORY

Stage 2 focuses on identifying and categorizing master data assets and their associated metadata. Organizations must begin by distinguishing between master data, transactional data, and reference data. This identification process typically involves: (1) engaging with key business units to define critical entities, and (2) conducting data source audits to determine the locations and structures in which master data is maintained. The outcome is a comprehensive data dictionary that consolidates master data along with its associated metadata into a unified reference source.

III.3 DATA QUALITY DIMENSIONS AND METRICS DESIGN

Stage 3 focuses on defining how the quality of data will be measured. This stage translates the business goals articulated in stage 1 into concrete, measurable data quality indicators. Each dimension should be mapped to specific business goals. These metrics serve as the foundation for sustained data stewardship, effective exception management, and the continuous improvement of data quality practices. The final output is a structured table featuring four main columns: Dimension, Measures, Calculation Technique, and Defined Threshold.

III.4 BUSINESS PROCESS MODELING AND GOVERNANCE SETUP

The next step is to embed these controls into organizational processes. Stage 4 formalizes the operational workflows by employing Business Process Modeling Notation (BPMN). This approach facilitates shared visibility between business and IT teams regarding the creation, validation, modification, and maintenance of master data across the enterprise. It operationalizes the MDM strategy through structured, visual workflows and clearly defined roles.

III.5 DATA PROFILING, MONITORING, AND EXCEPTION MANAGEMENT

Once the governance structure and process models are in place, organizations must manage the quality of their master data. Stage 5 operationalizes the data quality metrics defined in stage 3 by applying data profiling techniques, detecting anomalies, and implementing exception management workflows. These include: Column analysis, functional dependency discovery and cross-source comparison.

III.6 VALIDATION, TESTING, AND CONTINUOUS IMPROVEMENT

The final stage of the integrated Master Data Management framework focuses on validating the quality of master data. In contrast to the preceding project-driven stages, Stage 6 adopts a continuous approach aimed at sustaining MDM outcomes well beyond the initial implementation phase. This includes: Business rule validation, cross-system consistency checks and downstream output validation.

IV. CASE STUDY

The aim of our study is to examine the hypothesis that the integration of data quality principles into Master Data Management implementation enhances the reliability and consistency of patient information in healthcare organizations. The following section presents details contributions and their implementation in a real case study, following the steps outlined in figure 1. Study is taken in a regional hospital in January 2024. The case study operates in three services namely “Emergency Room”, “Blood service”, and “Labs”. The hospital system struggled with fragmented patient data, inconsistent quality, and rising regulatory compliance pressures. Disconnected electronic medical record systems led to duplicate patient records, incomplete or inaccurate data and delays in care efforts. To solve this, we propose to implement a six-phase MDM framework. First, we collaborate with stakeholders (including ER staff and lab technicians) to interview senior manager (heads of Operations) and staff using open questions. Questions focus on:

- How often bad or incomplete data is encountered.
- The effect of data errors on daily operations or tasks.

The senior manager explained critical gaps in patient blood type documentation, with 40% of records missing ABO/Rh data. This data incompleteness led to critical delays—ER physicians lost 15–20 minutes verifying blood types during hemorrhages, and labs often had to re-test samples due to unlinked or missing results in patient records. These inconsistent patient data caused frequent care delays, something IT could not have uncovered without direct involvement from frontline staff.

The table 1 outlines the strategic vision and corresponding goals for ensuring complete and reliable patient blood data within healthcare systems. It aligns each goal (G1–G4) with specific, measurable questions (Q1–Q7) to assess progress. The focus areas include improving data completeness, reducing record duplication, enhancing data synchronization between labs and Electronic Health Records (EHR), and boosting both patient safety and operational efficiency. Each question serves as a performance indicator to evaluate the success of MDM-related initiatives.

Table 1: Goals table.

Vision	Goals	Questions
Ensure complete and reliable patient blood	G1: improve data completeness	Q1: what percentage of patient records contains complete ABO/Rh blood type information? Q2: How many critical attributes (e.g., ID, demographics) are systematically missing?
	G2: reduce duplication of patient records.	Q3: what is the current duplicate rate of patient records in the Electronic Health Record compared to baseline?
	G3: enhance timeliness of data synchronization (lab ↔ EHR).	Q4: how quickly are lab results integrated into the Electronic Health Record after validation? Q5: What percentage of lab results fail to propagate automatically to the Electronic Health Record?
	G4: increase patient safety and operational efficiency	Q6: How often do care delays occur due to missing or inconsistent data? Q7: What is the reduction in re-testing rates for blood samples?

Source: Authors, (2025).

The team implemented strict data quality rules, mandating blood type verification before any surgery or transfusion and automatically rejecting unverified entries. They also developed a comprehensive data dictionary, cataloging all patient, provider, and asset data across systems, complete with metadata for consistency and clarity. All disparate sources were identified. To ensure clarity, goals must be defined in concrete and measurable terms. The purpose of this step is to translate the questions and goals identified in table 1 into data quality dimensions and associated measures, along with the appropriate calculation methods. A set of seven quality metrics were defined for answering each question, and a set of measurement methods were used for assessing such metric, as illustrated in table 2. Finally, the minimum thresholds required for each selected criterion is specified. The defined threshold must be high enough to ensure utility, but not so strict that remediation becomes infeasible.

Table 2: Data Quality Dimension

Question	Dimension	Metrics	Threshold
Q1	Completeness	% of patient records with ABO/Rh blood type filled	≥ 95%
Q2	Completeness	% of mandatory attributes populated per patient record	≥ 98%
Q3	Uniqueness	(Number of duplicate patient IDs ÷ Total patient records) × 100	Reduce duplicate patient records by 70% in 12 months
Q4	Timeliness	Average lab-to-EHR synchronization time (minutes)	≤ 5 minutes
Q5	Timeliness	(Number of lab results not propagated ÷ Total validated lab results) × 100	< 1%
Q6	Consistency	Average time lost per incident	Reduce delays by ≥ 70% in 12 months.
Q7	Accuracy	(Number of duplicate blood sample tests ÷ Total blood tests) × 100	reduce from 30% baseline to ≤ 2%

Source: Authors, (2025).

By applying data quality principles, we mapped key activities and scenarios involved in creating and updating patient records. Expert interviews and reference documentation informed this process, helping embed completeness, accuracy, and consistency across all data handling workflows. We redesigned workflows using BPMN models to support the implementation of Master Data Management. Now, when labs confirm a blood type, it auto-populates the EHR, with any conflicts flagged for pathologist review. Real-time dashboards track compliance, and weekly audits ensure ongoing data accuracy.

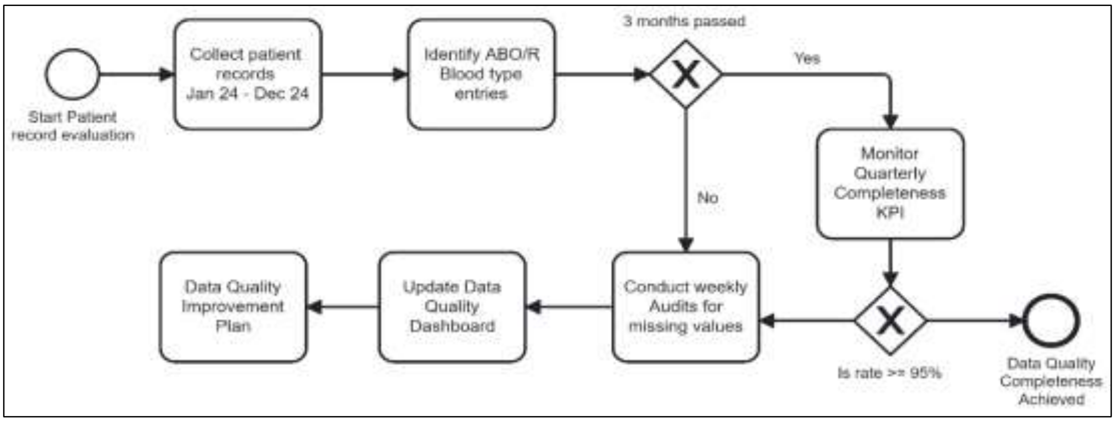

Figure 2: Healthcare data quality – Completeness – Camunda Modeler.
Source: [21].

Talend MDM tool is used for the implement of data quality and the construction of the MDM [22, 23]. From January to December 2024, we measured the percentage of patient records containing ABO/Rh blood type data, covering all clinical periods. During the spring quarter, weekly audits were conducted to identify missing values. To validate the findings, measurements were repeated and an average quality dimension rate was calculated for the year.
The following outlines how this phase applies to specific data quality metrics from Q1 to Q7:

- Q1 and Q2 – Completeness

To ensure completeness, this stage emphasizes the systematic tracking of patient records with mandatory attributes, such as ABO/Rh blood type and demographic data. Hospital departments have embedded these requirements into registration and lab systems. A data quality dashboard monitors completeness rates, with targets set at ≥95% and ≥98% respectively. These metrics are reviewed quarterly as part of KPI monitoring. Figure 2 illustrates how the completeness of patient blood type records (ABO/Rh) evolved throughout 2024. It measures the number of complete records out of a total of 1000, with a goal of reaching at least 950 (95%) after the MDM system was put in place, as shown in Figure 3.

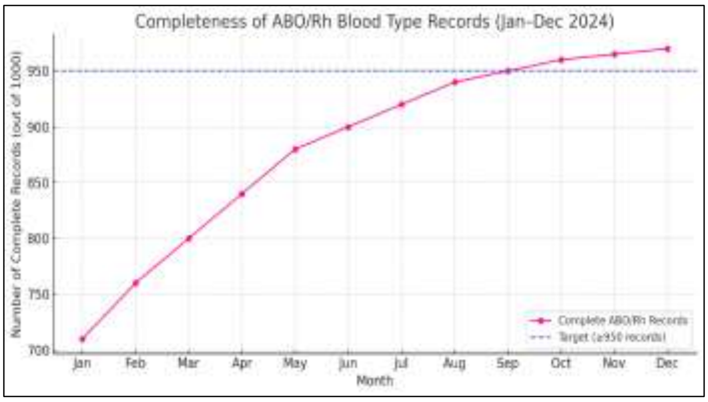

Figure 3: Pre and post completeness data quality.
Source: Authors, (2025).

- Q3 – Uniqueness

A 70% reduction in duplicate patient records over 12 months has been achieved through MDM's entity resolution capabilities, managed under stages 5 and 6 of the framework. Deduplication KPIs are regularly monitored and reported to the data governance board.

- Q4 and Q5 – Timeliness

Synchronization between lab systems and the EHR is actively monitored to ensure timeliness. Key performance indicators include average data propagation times (target ≤5 minutes) and error rates (target <1%). Metrics are logged in real time and audited monthly. Any deviations trigger immediate system diagnostics and process reviews, following the continuous improvement loop established for this phase.

- Q6 – Consistency

Time lost per incident due to data inconsistencies is a critical operational metric. In Phase 6, periodic incident tracking and response time analysis are conducted to achieve a ≥70% reduction in delays over 12 months, as shown in Figure 4. Consistency metrics are directly linked to process quality and are reviewed in cross-functional quality meetings.

Figure 4: Pre and post consistency.
Source: Authors, (2025).

- Q7 – Accuracy

Accuracy is monitored by tracking duplicate blood sample tests, with a reduction goal from a 30% baseline to ≤2%. Stage 6 includes clinical workflow audits and lab order reconciliation to measure and enforce accuracy. Alerts and automated checks are embedded within the EHR and lab information systems to support this objective. To support MDM implementation, change management efforts include a data quality directive endorsed by hospital leadership and distributed organization-wide. Training sessions, quick-reference guides, and ongoing communication campaigns promote a culture that treats data as a strategic asset, reinforcing alignment with data quality principles.

V. DISCUSSION

If the methodology directly addresses the identified failure factors, it aligns with state-of-the-art recommendations. This case study provides evidence for the framework's effectiveness by demonstrating its ability in tackling the challenges and solutions highlighted in recent literature. We presented our research methodology and analysis results to hospital managers, who found the insights both useful and constructive. The presentation enhanced their understanding of how to reduce duplicate patient records, address incomplete or inaccurate data, and minimize delays in care delivery.

- Evaluation of Data Quality.

The solution proposed in this paper places data quality at the core of the MDM process, starting with the identification of key quality dimensions, metrics, and thresholds. This approach ensures that data quality is treated not merely as a technical issue, but as a strategic business priority, with clear, measurable goals aligned to organizational objectives. By implementing the initial steps of the methodology, the organization established a shared master data dictionary and defined its data quality goals.

- Evaluation of Data Governance:

By initiating the MDM project with a unified vision and cross-functional input, the hospital significantly reduced the risk of misalignment, under-scoped implementations, and data quality failures. This early stage established a foundation for collaborative ownership, structured governance, and iterative development. The early involvement of both business and IT stakeholders fostered a shared vision and stronger alignment. BPMN modeling enhanced process transparency and understanding, supporting more effective training and documentation. The methodology explicitly emphasizes the need for early and continuous engagement from both business and IT throughout the project.

- Evaluation of Business and IT

The methodology's use of BPMN for process modeling aligns with best practices for bridging the gap between business and IT. MDM initiatives are often approached as purely technical projects, which can result in a disconnect between IT and business users. By adopting BPMN, the methodology produces visual workflows that are easily understood by both business analysts and technical teams. These models help uncover redundancies, delays, and risks within healthcare operations, enabling targeted improvements and more efficient use of resources.

The implementation of this integrated, process-driven MDM framework allowed the healthcare organization to significantly enhance patient data accuracy, operational efficiency, and regulatory compliance, while fostering a sustainable governance culture. The methodology's detailed focus on stakeholder engagement, process transparency through BPMN, and continuous monitoring offers a replicable and highly recommended approach for addressing MDM challenges related to data quality and fragmentation.

VI. CONCLUSION

In this paper, we proposed a novel framework that demonstrates how addressing insufficient data governance, fragmented data, and stakeholder resistance through a structured approach leads to measurable improvements in data quality, operational efficiency, and regulatory compliance—findings that align with current academic and industry research. This study introduced a six-stage Master Data Management framework that integrates strategic alignment with robust data quality governance. The framework was developed by merging principles from established data governance practices with stakeholder-centered methodologies and Business Process Modeling

Notation. Each stage targets a critical dimension of MDM implementation—from high-level visioning to operational quality control and continuous improvement. The framework promotes a balanced approach between strategic oversight and day-to-day execution, enabling organizations to build MDM capabilities that are both technically robust and business-aligned. It emphasizes cross-functional ownership, process transparency, and sustained quality management—effectively addressing many of the root causes of MDM failure identified in prior literature.

What distinguishes our framework is its integration of BPMN modeling, stakeholder-driven governance, and data quality metrics into a unified, actionable methodology. This combination enables organizations to evolve beyond static data governance strategies and adopt a more dynamic, role-aware, and metrics-driven execution of MDM programs. Hospital managers found our methodology and results highly valuable, particularly in improving their understanding of how to reduce duplicate patient records, address data completeness and accuracy issues, and minimize delays in care delivery.

However, the study's primary limitation lies in its validation through a single case study within the healthcare sector. While illustrative, it may not capture the full range of complexities present in other industries. Additionally, the framework's effectiveness is influenced by several contextual factors, including organizational readiness, technology infrastructure, and stakeholder engagement, all of which can vary significantly. Future research should explore multi-site implementations, cross-sectoral comparisons, and deeper integration with advanced analytics and metadata management platforms to further validate and enhance the framework's generalizability and impact.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Benkherourou Chafika and Abdelhabib Bourouis.
Methodology: Benkherourou Chafika and Abdelhabib Bourouis.
Investigation: Benkherourou Chafika and Abdelhabib Bourouis.
Discussion of results: Benkherourou Chafika and Abdelhabib Bourouis.
Writing – Original Draft: Benkherourou Chafika.
Writing – Review and Editing: Benkherourou Chafika and Abdelhabib Bourouis.
Resources: Benkherourou Chafika and Abdelhabib Bourouis.
Supervision: Abdelhabib Bourouis.
Approval of the final text: Benkherourou Chafika and Abdelhabib Bourouis.

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