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A Metrics-Driven Framework for Reliable Master Data

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ABSTRACT

Master Data Management (MDM) provides a way for organizations to effectively manage and share their core data. However, many MDM initiatives fail due to poor data quality. This paper proposes a practical framework designed to improve the development of MDM projects by focusing on data quality. Structured into five stages, the framework guides organizations through the implementation process in a logical order. In order to validate those guidelines, we conducted a study by applying with and without framework, the hospital significantly reduced medication errors and ensured safer patient transitions between care units. Beyond just healthcare, the framework gives organizations a clear way to bring business and IT goals together, improve transparency, and make MDM projects easier to plan and carry out.

Keywords: Master Data, MDM, Data Quality Dimensions, Master Data Management, Master Data Quality, Accuracy, Completeness, Timeliness.

INTRODUCTION

Businesses are handling an ever-increasing volume of data, while users expect quick and reliable access to that information. Applications in enterprises capture information in multiple formats, from structured database entries to unstructured text, images, and real-time sensor data. In the middle of all this complexity, master data, reliable, consistent information about things like customers, products, suppliers, and locations, acts as the backbone of a company's day-to-day operations and decision-making. It's so crucial that an entire discipline, master data management, exists to keep it clean, consistent, and well-governed [1, 2]. Master Data Management (MDM) is introduced to improve the quality of this core business data by consolidating it into a single managed repository. This repository acts as a "single source of truth" for applications across the organization [3]. Companies adopt MDM for many reasons, broadly defined as "the management of a consistent and uniform subset of business entities that describe the core activities of an enterprise" [1,4]. Effective MDM helps businesses drive digital transformation, enhances customer experiences by providing a 360° view of key entities, and lays a strong foundation for data governance that supports sustainable growth in a data-driven world.

However, like other IT initiatives, MDM projects are not immune to failure. Many of these failures stem from insufficient attention to data quality, such as the absence of proactive monitoring and the lack of well-defined quality measurements [5]. Other barriers include unclear roles within the data lifecycle [6] and limited focus on the measurement phase, which is critical for applying data quality metrics [7]. In addition, many organizations still lack comprehensive data management strategies. Although several MDM frameworks have been developed, most remain primarily technology-driven and do not provide practical approaches for integrating process modeling, real-time data quality management, and active stakeholder involvement throughout the MDM lifecycle [8].

To address these limitations, this study introduces a framework that puts continuous data quality, such as accuracy and uniqueness, at the center of MDM success. What makes it stand out is that it encourages active involvement from both business and IT stakeholders. The methodology is validated by a case study from a healthcare organization.

The paper is organized as follows. The next section reviews MDM implementation issues. Section 3 describes the research design and framework development. Section 4 presents the application of the methodology to the healthcare

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sector, illustrated by a case study. Section 5 reports the results and discussion. Finally, section 6 concludes and outlines directions for future research.

RELATED WORKS

Master data management (MDM) has become a prominent and widely discussed topic within the field of information systems. It is an all-encompassing, organization-wide strategy designed to enable companies to integrate, analyze, and leverage the full value of their data assets, no matter where the information originated [9]. 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 only essential for the successful adoption of Master Data Management systems but also one of the main advantages organizations achieve when MDM is implemented effectively [10]. However, Many MDM projects get abandoned because of persistent data quality problems, highlighting how crucial it is for everyone involved to work together and share common goals throughout the data quality process [11].

To meet growing demand, leading software providers are constantly enhancing their MDM solutions to support organizational needs [12]. Still, many platforms fall short on essential features, such as data profiling, that play a critical role in the early stages of MDM implementation for assessing and validating master data integrity [13,14].

This gap has led to closer collaboration between MDM vendors and data quality solution providers. Yet, no single platform fully meets all the requirements for comprehensive data quality and governance, highlighting the need for hybrid solutions and integrated strategies. Beyond the software layer, MDM is understood as the integration of technology, business processes, and governance practices [15]. Several models have attempted to structure MDM. For example, [16] identifies five core components: master data systems architecture, processes, organizational structure, data quality, and governance. Similarly, [17] outlines a framework with seven areas, including vision, governance, strategy, procedures, infrastructure, organizational roles, and performance measurement. Complementarily, [18] identifies three primary domains-organization, process, and systems-as central to developing MDM capability. Building on this, [19] proposes an eight-stage, process-oriented methodology designed for the microfinance industry with a focus on improving data quality. Likewise, [20] introduces a ten-stage model that includes steps such as defining objectives and core data, establishing data standards, designing governance frameworks, planning MDM metrics and architecture, organizing communication and training, setting up maintenance procedures, and specifying functional and operational capabilities. These studies show why the data-quality strategy must be set early.

Master Data Management efforts often fall short due to ongoing data quality issues like errors, inconsistencies, duplicate records, and missing information. These challenges weaken the trustworthiness and overall value of master data repositories. As [21] emphasizes, enhancing data quality is not solely a technical task but demands sustained organizational commitment. Effective approaches to these challenges include structured staff training, ongoing cross-team communication, routine data quality monitoring, and the use of exception handling and duplicate detection tools [22]. Poor data quality often stems from fragmented data sources, outdated legacy systems, and inconsistent data entry practices [23]. In addition, gaps between functional requirements and the actual capabilities of MDM systems can create inefficiencies and lead to redundant data [24].

Weak governance structures frequently lead to unclear data ownership, vague stewardship roles, and inconsistent enforcement of data standards [14]. Research consistently highlights governance shortcomings as a major obstacle to successful MDM implementation [25]. Typical indicators of governance failure include poor coordination between technical and business teams, disjointed data management practices, and a mismatch between MDM tools and organizational needs, particularly during iterative deployment phases [25,26]. To overcome these challenges, [27] recommends incremental and scalable governance strategies, starting small and expanding gradually. Importantly, governance frameworks must be adapted to an organization’s operational context to ensure both relevance and effectiveness [28].

MDM projects also often struggle with poor planning and sequencing, which can lead to financial losses and operational inefficiencies [29]. As [30] observes, IT-driven MDM initiatives that lack broad organizational

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engagement are particularly vulnerable to failure. Without enterprise-wide buy-in, governance structures risk becoming informal and siloed, thereby reducing the chances of achieving sustainable data quality improvements.

The literature consistently emphasizes that data quality and governance are central to the success of MDM initiatives. Achieving this success requires more than advanced tools—it also depends on strategic alignment, disciplined processes, and collaborative governance frameworks. While methodologies and technologies have advanced considerably, the ongoing challenge lies in integrating organizational, technical, and strategic elements, especially when adapting MDM solutions to evolving business needs.

METHODS

In this section, we provide a detailed description of our proposed methodology. The schematic representation of this approach is shown in Figure 1.

Figure 1: Framework Steps

To effectively manage data quality on an ongoing basis, we recommend developing the organization's vision and quality methodology side by side. This will involve several key steps. First, all stakeholders, from both business and IT, will be actively engaged to uncover the root causes of data quality problems and share their expectations about when and how data should be usable.

To support this process, we conducted structured and semi-structured interviews with departmental staff and related units. These interviews enabled a thorough analysis of the department's operational landscape, revealed critical data challenges, and captured diverse stakeholder perspectives. The outcome of this step will be a table that documents the organization's vision, objectives, and key questions, constructed using the additional insights obtained in step 2.

Stage 2 focuses on identifying master data assets. At this stage, master data is catalogued along with the applications that generate it and those that consume it. This process relies heavily on manual assessments conducted by data stewards and business analysts. The outcome is a comprehensive data dictionary that consolidates master data along with its associated metadata into a unified reference source.

The third stage establishes the data quality dimensions and the metrics used to assess them. Business objectives identified in Stage 1 are translated into quantifiable dimensions, such as completeness, timeliness, and accuracy, along with corresponding metrics and calculation methods. Each dimension is then linked to relevant business goals and master data attributes, promoting alignment between organizational priorities and data quality efforts. The final output is a structured table featuring four main columns: Dimension, Measures, Calculation Technique, and Defined Threshold.

Once governance frameworks and process models are in place, organizations must take an active role in maintaining master data quality. In Stage 4, the data quality metrics outlined in stage 3 are put into practice through data profiling, anomaly detection, and exception management workflows. This stage typically leverages profiling dashboards and automated alerts to identify irregularities and enable prompt corrective action.

The final stage of the MDM framework is dedicated to the continuous monitoring and maintenance of master data quality. In contrast to earlier, project-focused phases, this stage is ongoing, aiming to ensure that data quality and MDM outcomes are sustained well beyond the initial implementation. Important tasks in this stage include validating business rules, checking consistency across systems, conducting regular audits, analyzing key performance indicators, and gradually adjusting quality thresholds.

CASE STUDY

This study aims to test whether incorporating data quality principles during Master Data Management implementation improves the reliability and consistency of patient information in healthcare organizations. The

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proposed framework was tested and validated in a regional hospital. The next section highlights its key contributions and how it was applied in practice. During the implementation process, three major data quality challenges emerged:

1. Fragmented systems and duplicate prescriptions: limited integration between hospital systems occasionally resulted in physicians issuing overlapping prescriptions. An analysis found that 14% of medication orders were duplicated across departments, increasing the risk of confusion, missed doses, and, in some cases, unsafe re-administration.
2. Delays in synchronizing orders between the EHR and pharmacy system: time lags in updating medication orders between the electronic health record (EHR) and pharmacy systems sometimes caused nurses to act on outdated information. This issue was especially critical during shift transitions, heightening the risk of medication errors.
3. Inaccurate medication records: occasional errors in medication documentation led to incorrect dosage administration, posing threats to patient safety and reducing overall operational efficiency.

To address these challenges, the MDM framework was used to establish data quality goals aligned with the hospital's operational needs. Key stakeholders, including pharmacists, nurses, and clinical informatics personnel, were consulted through interviews to surface pain points, clarify expectations, and identify areas for improvement. Drawing on these insights, hospital leadership defined the following vision:

"To ensure complete, accurate, and timely patient medication data for safe and efficient care delivery."

This vision was then translated into three measurable data quality goals, effectively linking strategic intent with actionable outcomes.

- G1: Reduce duplication of medication orders.
- G2: Enhance timeliness of order synchronization.
- G3: Improve accuracy of medication administration data.

Three quality questions were developed in order to clarify quality goals.

Table 1: Goals table

Goals	Question
G1: Reduce duplication of medication orders	Q1: What is the current duplicate rate of medication orders across systems??
G2: Enhance timeliness of order synchronization	Q2: What percentage of medication orders fail to update within 5 minutes?
G3: Improve accuracy of medication administration data	Q3: What is the rate of incorrect or outdated medication records?

Each goal was mapped to relevant data quality dimensions, accompanied by specific metrics and clearly defined thresholds. To put these goals into practice, the hospital implemented the Pentaho MDM platform [31], enabling the management of data quality rules and the execution of deduplication workflows.

- *Q1 – Uniqueness (Deduplication):*
  MDM rules were configured to identify and merge medication records sharing the same patient ID, timestamp, and drug code. This approach helped eliminate duplicate orders and improved the visibility of prescriptions across departments.
  Metric: (Duplicate medication orders ÷ Total medication orders) × 100.
  Threshold: 85% reduction within 9 months
- *Q2 – Timeliness:*

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Real-time synchronization between the EHR and pharmacy systems was achieved using message queues and middleware integration. Any delays were systematically logged, audited on a monthly basis, and continuously tracked against established performance thresholds.
Metric: (Medication orders delayed >5 min ÷ Total orders) × 100.
Threshold: ≤2% of orders delayed beyond 5 minutes

- *Q3-Accuracy:*
  Medication administration workflows were redesigned to incorporate dose confirmation and digital verification. Automated alerts flagged outdated or missing entries.
  Metric: (Incorrect or incomplete medication administrations ÷ Total administrations) × 100.
  Threshold: ≤1%

Data quality was continuously monitored throughout 2023. Weekly audits were conducted during the winter, followed by a second round of validation in the summer quarter to assess long-term sustainability. To measure overall progress, the annual average across all quality dimensions as calculated.

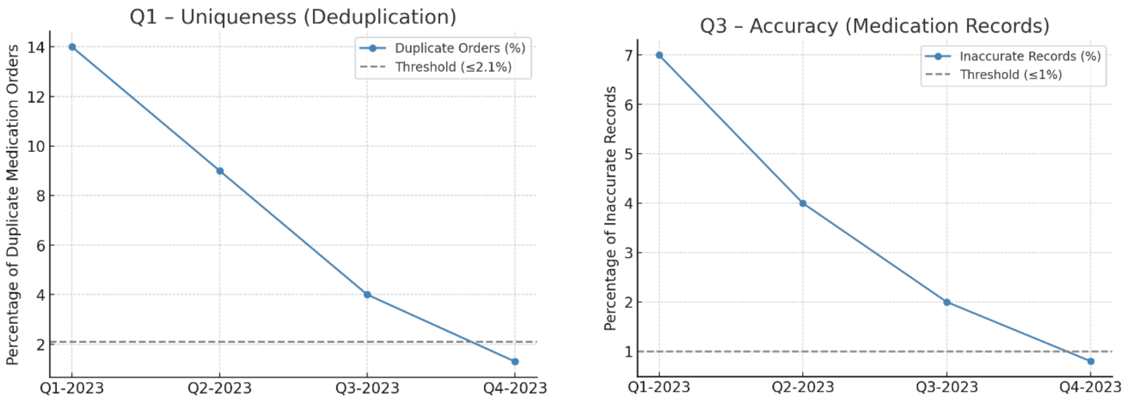

Figure 2: Pre and post MDM implementation

To ensure long-term impact, the hospital implemented a series of organizational initiatives designed to reinforce and sustain the MDM framework.

- A hospital-wide data quality directive was launched and formally endorsed by senior leadership.
- Dashboards were developed to visualize key data quality indicators and support ongoing monitoring.
- A data governance council was established, comprising representatives from IT, pharmacy, and clinical leadership, to oversee governance activities.
- Staff were provided with training sessions and quick-reference materials to embed the new workflows into daily practice.

Results over 12 Months:

- Duplicate medication orders decreased from 14% to 1.3%.
- Medication synchronization delays dropped from 41% to 1.4%.
- Inaccurate medication records were reduced from 7% to 0.8%.

DISCUSSION

This case study illustrates how a metrics-driven MDM framework can lead to tangible improvements in data accuracy, timeliness, and uniqueness, particularly in the high-stakes context of medication administration. Focusing on data quality directly at the point of care, the hospital achieved notable improvements in patient safety, operational efficiency, and overall data consistency across the system, all without needing major technology upgrades.

The methodology and findings were shared with hospital leadership, who regarded the analysis as both constructive and actionable. It offered clearer strategies for tackling persistent issues such as duplicate patient records, incomplete or inaccurate data, and delays in care delivery.

The proposed solution establishes data quality as the foundation of the MDM process, beginning with the identification of quality dimensions, metrics, and thresholds. This approach shifts the perception of data quality from a purely technical concern to a strategic business priority, grounded in measurable goals that align directly with the organization's broader objectives.

CONCLUSION

This paper introduced a metrics-driven MDM framework as a solution to persistent data quality challenges. By addressing issues such as fragmented data and stakeholder resistance through a structured approach, the framework demonstrated measurable improvements in data quality, operational efficiency, and regulatory compliance—findings consistent with both academic and industry research. The framework supports a critical dimension of MDM implementation, extending from high-level vision setting to operational quality control and continuous improvement, with a targeted emphasis on accuracy, timeliness, and uniqueness. Validation through a healthcare case study confirmed its effectiveness, showing substantial reductions in duplicate records and synchronization delays. These results underscore how a focused, practical approach can deliver strong outcomes. While completeness and other dimensions were not explicitly addressed, the framework provides a solid foundation for building reliable master data systems. It reinforces the importance of cross-functional ownership, process transparency, and sustained quality management, addressing many of the root causes of MDM failure highlighted in prior literature. Importantly, the framework is adaptable, as it is mapped to data quality dimensions that organizations can apply directly to their own challenges.

Future research should test this framework across diverse sectors and investigate how incorporating additional data quality dimensions may interact with and strengthen the core focus on accuracy, timeliness, and uniqueness.

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