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# Generative AI-Powered Framework for Scalable and Real-Time Data Quality Management in Databricks

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## ABSTRACT

In today's data-driven field, ensuring high data quality is essential for accurate analysis and informed decision-making. Traditional data quality management methods are often labor-intensive, difficult to scale, and struggle to handle the vast and complex datasets prevalent in modern organizations. This paper proposes a novel framework that integrates Generative AI within the Databricks platform to enhance data quality management across critical dimensions, including accuracy, consistency, completeness, and timeliness. Leveraging the scalable infrastructure of Databricks, our solution employs Generative AI to automatically detect and correct data anomalies, impute missing values, and generate validation rules based on natural language commands, significantly reducing the need for manual intervention. Extensive experiments were conducted to compare the proposed approach with industry-standard data quality tools, including Ataccama ONE, Informatica Data Quality, IBM InfoSphere QualityStage, Talend Data Quality, and Soda SQL. Results demonstrate substantial improvements in data quality metrics, with our framework achieving up to 9.41% higher accuracy, 9.09% better timeliness, and a 7.78% increase in completeness over baseline scores. Additionally, our system's ability to operate in real-time, coupled with seamless integration in Databricks, makes it a powerful, adaptive, and cost-effective solution for large-scale, dynamic data environments. This research provides valuable insights into the capabilities of Generative AI in data quality management, setting the stage for future advancements in automated data integrity solutions.

## General Terms

Large-Scale Data Environments, Machine Learning in Data Quality, Scalable Data Solutions

## Keywords

Data Quality Management, Generative AI, Databricks, Real-Time Data Processing, Automated Data Cleansing, Anomaly Detection, Data Imputation

## 1. INTRODUCTION

In today's digital field, data has become an essential asset driving decision-making, operational efficiency, and strategic development across industries. As organizations increasingly rely on data analytics. The quality of data becomes critical to producing reliable and actionable insights. High-quality data enables businesses to make informed decisions and engage in accurate predictive analysis. This fosters a competitive edge by allowing organizations to act on precise forecasts. However, when data quality is compromised, the impact is substantial. It often resulting in flawed conclusions, financial losses, and inefficiencies [8]. The need for rigorous data integrity measures has become even more pressing in large-scale data environments. The errors in data can multiply and cause widespread disruptions. Addressing these challenges requires an approach that can manage data integrity dynamically and efficiently, especially as data continues to expand in volume, variety, and complexity [13].

Traditional data quality assurance methods typically involve manual data cleaning, static validation checks, and rule-based monitoring systems. While these approaches have been effective in smaller, controlled environments, they are often labor-intensive, costly, and prone toS error. As data continues to grow exponentially, these methods fall short in terms of scalability and adaptability [22]. The expansion of Big Data introduces new challenges, making traditional approaches to data quality insufficient for real-time applications and large data volumes. Databricks, designed to handle extensive datasets with speed and flexibility, offers a promising foundation for integrating advanced AI-driven approaches. Which could revolutionize data quality management by reducing manual intervention and improving scalability and accuracy [26].

This research focuses on the limitations of conventional data quality methods in maintaining reliable data within increasingly complex environments. Traditional approaches largely rely on static rules and manual interventions to ensure data accuracy, consistency, and completeness [21]. However, these methods lack the flexibility and adaptability necessary to respond to real-time data inconsistencies in dynamic pipelines. As real-time analytics and complex data workflows become standard in data-driven organizations, traditional data quality practices risk falling short of organizational demands. This creates a critical need for solutions that not only streamline data quality processes but also adapt to changing data characteristics in real time. This presents an opportunity to integrate Generative AI into Databricks workflows, enabling enhanced data quality by addressing anomalies and inconsistencies more effectively than traditional approaches alone [9].

Many organizations today utilize Databricks for its ability to process and analyze large datasets quickly and efficiently. While some advanced tools incorporate automation to manage data quality, these tools often lack the adaptability needed for continuous, real-

time quality assurance. Current solutions cannot dynamically adjust to detect and resolve data anomalies as they arise [17]. By embedding Generative AI within Databricks workflows, data quality processes can evolve to meet the demands of modern data environments. Generative AI offers capabilities for data synthesis, validation, and correction that traditional methods lack. This integration provides a significant advancement in data quality management, enabling organizations to manage data quality with greater precision, scalability, and efficiency, and allowing teams to handle data complexities with minimal human intervention [4].

This study proposes a novel framework that uses Generative AI within Databricks to augment traditional data quality methods. Unlike static validation checks, the proposed framework utilizes Generative AI's capacity to generate, validate, and correct data dynamically within Databricks environments. This enables continuous data monitoring and real-time anomaly detection, offering a level of adaptability that static methods cannot achieve. The integration of Generative AI into Databricks workflows enhances traditional data quality processes by enabling data engineers, solution architects, and data scientists to monitor and correct data quality issues seamlessly. By incorporating Generative AI into a scalable platform like Databricks, our approach aims to improve the accuracy, consistency, and completeness of data while minimizing the need for manual quality checks.

The aim of this research is to investigate the role of Generative AI within Databricks as a complement to traditional data quality management methods. The study examines its potential to transform data integrity practices in large-scale data environments.

The research objectives are as follows:

(1) To examine how Generative AI within Databricks enhances data quality dimensions such as accuracy, consistency, completeness, and uniqueness.

(2) To assess the impact of integrating Generative AI with Databricks on organizational workflows, particularly focusing on roles like data engineers, solution architects, and data scientists.

(3) To identify emerging trends in Generative AI applications within Databricks, particularly through the use of LLMs for data quality management.

This research is significant because it addresses an underexplored intersection between AI and data quality within the Databricks platform. By examining the integration of Generative AI into Databricks workflows, this study offers insights that may help organizations improve data quality, streamline workflows, and enhance decision-making. The findings are expected to contribute foundational knowledge for future innovations in data quality management, positioning Generative AI as a key tool for handling complex data environments within Databricks.

The remainder of this paper is organized as follows. Section 2 provides a review of AI, Generative AI, and Databricks in relation to data quality. Section 3 outlines the methodology, detailing data sources, research design, and analytical techniques used. Section 4 provides the details of the experiments. Section 5 presents the findings of this study. Finally, Section 6 concludes with insights, practical implications, and recommendations for future research.

## 2. LITERATURE REVIEW

Recent advancements in Generative AI, particularly within scalable data platforms like Databricks, are reshaping data quality management. Traditional methods for data quality rely heavily on manual cleaning and rule-based validations. These approaches are time-consuming and lack scalability, especially with the exponential growth in data volume. According to Gupta and Yip, integrating Generative AI with Databricks introduces new possibilities for automating data quality tasks [10]. They suggest that Generative AI enhances data synthesis, validation, and real-time anomaly detection, providing more efficiency than conventional methods.

Maxwell discusses the transformative role of automation in data-driven processes, highlighting how AI can reduce manual effort and improve accuracy [20]. Dhoni explores the role of Generative AI in real-time anomaly detection and data validation [6]. His findings show that Generative AI can automate processes traditionally handled by data teams, reducing costs and increasing operational efficiency. Dhoni also emphasizes the economic value of using AI-driven approaches, particularly for organizations with limited resources [7]. These studies underscore the value of AI in automating and optimizing data quality tasks, but they lack integration within real-time platforms like Databricks.

Cloud-based platforms further enhance the utility of Generative AI in data quality. Cohan discusses how cloud platforms provide the computational power needed for real-time data processing and validation [5]. By leveraging the cloud, platforms like Databricks can process large data volumes rapidly, supporting Generative AI's dynamic data management capabilities. Cohan's insights reveal the scalability cloud-based solutions offer, making advanced AI capabilities accessible for a wide range of organizations.

Research by Jindal et al. focuses on turning databases into active engines for data generation and validation [16]. They propose that databases using Generative AI can autonomously maintain and enhance data quality. This transformation allows databases to handle real-time inconsistencies without relying on static validation rules. Such an approach aligns with Databricks' real-time processing capabilities, which can incorporate these active AI models for continuous data quality management [2].

LLMs also play a crucial role in simplifying data quality management. Keisala discusses using LLMs as no-code interfaces, making data validation and quality checks more accessible to non-technical users [18]. LLMs generate validation rules based on natural language prompts, eliminating the need for specialized coding skills. When implemented within Databricks, these models can enable broader collaboration across teams, facilitating continuous data quality management with minimal technical barriers [12].

Dhoni further examines the integration of Generative AI within Databricks for scalable data analytics [1]. He presents a framework where Generative AI monitors and corrects data inconsistencies in real time. This approach reduces manual intervention while enhancing data accuracy, timeliness, and consistency across large datasets. His framework demonstrates how Databricks can support continuous data quality management through a scalable and automated system.

Vesjolijs proposes an E(G)TL model that integrates Generative AI into the data transformation process [25]. By generating synthetic data to fill gaps and correct inconsistencies, this model can enhance data completeness and accuracy. When applied within Databricks, the E(G)TL model optimizes data workflows, providing a streamlined approach to maintaining data quality in complex, multivariate systems.

Mahajan et al. present a Generative AI-powered recommendation engine within Spark clusters, focusing on efficient data processing and quality management [19]. This system dynamically adapts resource allocation to support high-quality data processing in large environments, aligning well with Databricks' scalable infrastructure. Their work illustrates the practicality of embedding Genera-

tive AI directly within data processing frameworks, enhancing both data quality and operational efficiency.

Hosea and I.T. Student explore converting traditional data warehouses into active knowledge bases capable of Retrieval-Augmented Generation (RAG) [11]. They discuss how applying AI to validate and transform data continuously enhances data quality. Implementing this within Databricks can support organizations in building dynamic, real-time data systems that improve with each interaction.

Despite these advances, a clear gap exists. Current research lacks a cohesive framework for integrating Generative AI within Databricks to create a fully automated, adaptive data quality solution. Most solutions address isolated aspects of data quality, but they do not offer an end-to-end system capable of handling dynamic, high-volume data environments in real time. Our research fills this gap by proposing a comprehensive model that embeds Generative AI directly within Databricks workflows. This model aims to provide continuous data validation, anomaly correction, and adaptability at scale, supporting seamless data quality management in complex, real-time data ecosystems.

## 3. METHODOLOGY

This study develops a comprehensive Generative AI-enhanced data quality management framework within Databricks. Our methodology integrates three primary methods to monitor, validate, and improve data quality in real-time using Databricks' scalable environment. This framework uses Generative AI for dynamic anomaly detection, data imputation, and consistency checks. The primary dimensions addressed in this study are accuracy, consistency, completeness, and timeliness. Each dimension is formally defined, quantitatively evaluated, and integrated into Databricks workflows to construct a robust and adaptive data quality management system.

### 3.1 Data Quality Metrics

To rigorously monitor and quantify data quality in real-time streaming environments, this study defines a formal suite of metric functions

$$Q = \{Q_{\text{accuracy}}, Q_{\text{consistency}}, Q_{\text{completeness}}, Q_{\text{timeliness}}\}$$

for each incoming data batch

$$D = \{d_1, d_2, \ldots, d_n\},$$

where each $d_i \in \mathbb{R}^m$ represents an individual data record consisting of $m$ attributes. Let $G = \{g_1, g_2, \ldots, g_n\}$ be the corresponding ground truth data set. For each metric $Q_k \in Q$, a numerical score $S_k(D) \in [0, 1]$ is computed to reflect the quality of dataset $D$ with respect to dimension $k$.

*3.1.1 Accuracy Metric.* Let $\delta_i \in \{0, 1\}$ be a correctness indicator defined by:

$$\delta_i = \begin{cases} 1 & \text{if } d_i = g_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The overall accuracy score is:

$$S_{\text{accuracy}} = \frac{1}{n} \sum_{i=1}^{n} \delta_i \tag{2}$$

For multi-attribute records $d_i = (x_1, x_2, ..., x_m)$, attribute-level accuracy $\delta_i^j$ for feature $j$ can be evaluated and averaged:

$$\delta_i^j = \mathbb{I}(x_j^{(i)} = g_j^{(i)}), \quad S_{\text{accuracy}} = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} \delta_i^j \tag{3}$$

*3.1.2 Consistency Metric.* Let $d_i^{(t)}$ and $d_i^{(t+1)}$ denote successive observations of record $i$. The consistency deviation is:

$$\Delta_i = \frac{1}{m} \sum_{j=1}^{m} |x_j^{(i,t+1)} - x_j^{(i,t)}| \tag{4}$$

The normalized consistency score is:

$$S_{\text{consistency}} = 1 - \frac{1}{n} \sum_{i=1}^{n} \min\left(1, \frac{\Delta_i}{\tau_c}\right) \tag{5}$$

where $\tau_c$ is a threshold for acceptable change magnitude.

*3.1.3 Completeness Metric.* Define $m_{ij} \in \{0, 1\}$ such that:

$$m_{ij} = \begin{cases} 1 & \text{if } x_j^{(i)} \text{ is missing} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

The completeness score is:

$$S_{\text{completeness}} = 1 - \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} m_{ij} \tag{7}$$

This ensures that each attribute per record contributes equally to the completeness metric.

*3.1.4 Timeliness Metric.* Assume each record $d_i$ has a timestamp $t_i$, and let $T_i$ be the expected arrival time. Define time delay $\Delta t_i = t_i - T_i$. The exponential decay model gives:

$$S_{\text{timeliness}} = \frac{1}{n} \sum_{i=1}^{n} \exp(-\alpha |\Delta t_i|) \tag{8}$$

where $\alpha > 0$ controls penalty steepness. To penalize late arrivals more harshly:

$$S_{\text{timeliness}} = \frac{1}{n} \sum_{i=1}^{n} \begin{cases} \exp(-\alpha |\Delta t_i|) & \text{if } t_i \leq T_i \\ \beta \cdot \exp(-\alpha |\Delta t_i|) & \text{if } t_i > T_i \end{cases} \tag{9}$$

with $0 < \beta < 1$ as a delay penalty factor.

*3.1.5 Overall Data Quality Score.* The aggregate data quality score is computed as a convex combination:

$$S_{\text{total}} = \sum_{k \in Q} w_k \cdot S_k(D) \tag{10}$$

subject to the constraint:

$$\sum_{k \in Q} w_k = 1, \quad w_k \geq 0 \; \forall k \tag{11}$$

The weight vector $\mathbf{w} = [w_{\text{accuracy}}, w_{\text{consistency}}, w_{\text{completeness}}, w_{\text{timeliness}}]$ is adjustable based on application requirements. All scores $S_k \in [0, 1]$ make $S_{\text{total}}$ interpretable and bounded.

This formalization provides a precise, low-level structure to evaluate and optimize data quality within Databricks in real time using Generative AI-driven modules.

### 3.2 Method 1: Natural Language Instructions with SODA GPT

This method introduces a mechanism for translating natural language (NL) quality instructions into executable validation logic within the Databricks environment using SODA GPT. It allows non-technical users to define high-level quality expectations, which are automatically compiled into SQL or YAML queries that are run over distributed data partitions.
Let $\mathcal{I} = \{I_1, I_2, \ldots, I_m\}$ be a sequence of natural language instructions issued by a user or application, where each $I_j$ denotes a quality rule such as "Ensure there are no null values in the email field" or "Verify that transaction amounts are non-negative."
Each instruction $I_j$ is processed by SODA GPT through the following mapping:

$$\phi : I_j \mapsto \mathcal{Q}_j, \tag{12}$$

where $\phi$ is the transformation function and $\mathcal{Q}_j \in \{\text{SQL}, \text{YAML}\}$ denotes the machine-interpretable query derived from $I_j$.
For a dataset $D = \{d_1, d_2, \ldots, d_n\}$, each query $\mathcal{Q}_j$ defines a boolean function:

$$Q_j(d_i) = \begin{cases} 1, & \text{if } d_i \text{ satisfies } \mathcal{Q}_j \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

The compliance score $C_j$ for query $\mathcal{Q}_j$ is computed as:

$$C_j = \frac{1}{n} \sum_{i=1}^{n} Q_j(d_i) \tag{14}$$

This scalar $C_j \in [0, 1]$ measures the proportion of records in $D$ that meet the condition encoded by $\mathcal{Q}_j$.
For example, a user-specified instruction:

$$I_j = \text{"Ensure there are no duplicate orders"}$$

is mapped by SODA GPT to:

$$\mathcal{Q}_j = \texttt{SELECT order\_id, COUNT(*) FROM orders GROUP BY order\_id HAVING COUNT(*) > 1;}$$

The execution of $\mathcal{Q}_j$ across distributed Spark partitions is handled natively in Databricks. Let $P = \{P_1, \ldots, P_k\}$ be the partitioned data chunks. Each $P_l$ executes $\mathcal{Q}_j$, and the intermediate results $R_l$ are gathered:

$$R = \bigcup_{l=1}^{k} \mathcal{Q}_j(P_l) \tag{15}$$

All non-compliant records are logged in a structured audit table $\mathcal{A}_j$ within a Delta Lake architecture:

$$\mathcal{A}_j = \{d_i \in D \mid Q_j(d_i) = 0\} \tag{16}$$

In real-time deployments, a quality compliance threshold $\tau_j \in [0, 1]$ is pre-defined for each rule. If $C_j < \tau_j$, an alert is automatically raised in SODA Cloud and forwarded to the responsible data team. The remediation workflow can then be initiated, either through manual correction or via downstream automation pipelines.
Additionally, historical compliance trends can be analyzed by maintaining a temporal log of scores:

$$\mathcal{T}_j = \{(t_1, C_j^{(t_1)}), (t_2, C_j^{(t_2)}), \ldots\} \tag{17}$$

This log enables monitoring of drift or degradation in data quality over time, providing feedback for model retraining or pipeline adjustment.
Through this method, SODA GPT operationalizes high-level domain expectations in an accessible and scalable manner, bridging the gap between data consumers and data engineering teams in dynamic data environments.

### 3.3 Method 2: Databricks and Azure Data Quality Framework

To manage and enhance data quality at scale, this method integrates Databricks with Azure-native services—specifically Azure Data Factory (ADF), Azure Synapse, and Azure Monitor—to construct a modular, multi-layered data quality (DQ) framework. The system is architected to monitor and correct data along critical dimensions, namely accuracy, uniqueness, and timeliness, while maintaining operational responsiveness.
Let $D = \{d_1, d_2, \ldots, d_n\}$ denote the incoming data batch at ingestion time $t$, with each record $d_i \in \mathbb{R}^m$ representing a feature vector of $m$ attributes. The overall pipeline is decomposed into three functional layers: ingestion layer, validation layer, and correction layer.

*3.3.1 Ingestion Layer: Real-Time Data Acquisition and Timestamping.* This layer orchestrates the real-time ingestion of data using Azure Data Factory (ADF) and Event Hubs, routing each batch $D_t$ to Databricks. Every record $d_i$ is enriched with a timestamp attribute $t_i$, representing the arrival time.
Let the expected ingestion time be $T_i$, the actual arrival time be $t_i$, and define the temporal deviation $\delta_i = |T_i - t_i|$. The timeliness quality score is computed for batch $D_t$ using exponential decay as:

$$S_{\text{timeliness}}(D_t) = \frac{1}{n} \sum_{i=1}^{n} \exp(-\alpha \delta_i) \tag{18}$$

where $\alpha > 0$ is a tunable decay rate penalizing late data. A lower $\delta_i$ implies a higher score, favoring punctual records. Data that falls below a minimum threshold $S^{\text{min}}_{\text{timeliness}}$ is flagged for delayed processing and downstream correction.

*3.3.2 Validation Layer: Uniqueness and Accuracy Enforcement.* In this layer, data is validated through distributed rules executed on Databricks clusters using Apache Spark. Each record $d_i$ is assigned a unique fingerprint $U(d_i)$, often computed using hash-based tokenization:

$$U(d_i) = \text{Hash}(d_i[a_1], d_i[a_2], \ldots, d_i[a_k]) \tag{19}$$

where $\{a_1, \ldots, a_k\} \subset \{1, \ldots, m\}$ are the key attributes determining uniqueness (e.g., transaction ID, user ID). Duplicate records are detected via:

$$\mathcal{M}_u = \{d_i \in D_t \mid \exists\, d_j \in D_t,\ i \neq j \text{ and } U(d_i) = U(d_j)\} \tag{20}$$

The uniqueness score is then:

$$S_{\text{uniqueness}}(D_t) = 1 - \frac{|\mathcal{M}_u|}{n} \tag{21}$$

High uniqueness scores indicate the dataset contains distinct entries. Violations are logged to an audit table $\mathcal{A}_u$ and queued for deduplication in the correction layer.
To validate accuracy, known ground truth mappings $G = \{(d_i, g_i)\}$ are optionally employed (e.g., reference tables). The ac-

curacy score is:

$$S_{\text{accuracy}}(D_t) = \frac{1}{n}\sum_{i=1}^{n}\mathbb{I}(d_i = g_i) \tag{22}$$

where $\mathbb{I}$ is the indicator function, returning 1 if values match the ground truth $g_i$, and 0 otherwise.

*3.3.3 Correction Layer: Anomaly Rectification and Re-Evaluation.* This layer is triggered when a metric $S_k(D_t) < \tau_k$, where $\tau_k \in [0,1]$ is the pre-defined quality threshold for metric $k \in \{\text{accuracy}, \text{timeliness}, \text{uniqueness}\}$.
Let $\mathcal{F}_k = \{d_i \in D_t \mid Q_k(d_i) = 0\}$ denote the set of failing records for quality dimension $k$. Each record $d_i \in \mathcal{F}_k$ is passed through a Generative AI module $\mathcal{G}_\theta$, parameterized by $\theta$, to generate a corrected version $\hat{d}_i$:

$$\hat{d}_i = \mathcal{G}_\theta(d_i, k) \tag{23}$$

The corrected batch $\hat{D}_t = \{\hat{d}_i \mid d_i \in \mathcal{F}_k\} \cup \{d_j \in D_t \setminus \mathcal{F}_k\}$ is re-evaluated using the same scoring metrics. The updated scores $S_k^{\text{corrected}}(D_t)$ must satisfy:

$$S_k^{\text{corrected}}(D_t) \geq \tau_k \quad \forall k \tag{24}$$

Records still failing quality checks after two iterations are moved to quarantine storage and flagged for human review.

*3.3.4 Audit and Monitoring Layer.* Azure Monitor tracks all metrics $S_k(D_t)$ and compliance over time $t$. A temporal quality trace is stored as:

$$\mathcal{T}_k = \{(t_1, S_k^{(t_1)}), (t_2, S_k^{(t_2)}), \ldots\} \tag{25}$$

Alerts are generated when a persistent drop is detected:

$$\exists\, \Delta > 0 \text{ such that } S_k^{(t_{i+1})} - S_k^{(t_i)} < -\Delta \text{ for } p \text{ consecutive } t_i \tag{26}$$

This log enables trend analysis, automated rollback, and feedback for retraining Generative AI models using production data.

*3.3.5 Ingestion Layer.* The ingestion pipeline $I(D)$, managed by Databricks and Azure Data Factory, ensures data arrives on time. Each data batch is timestamped, and timeliness is monitored by the timeliness score $S_{\text{timeliness}}$ calculated at ingestion. This enables continuous quality checks and timely ingestion of new data batches.

*3.3.6 Uniqueness Checks.* Each data record $d_i$ receives a unique identifier $U(d_i)$ to prevent duplication. During ingestion, Generative AI generates hash codes or unique keys, ensuring distinct records within Databricks. The uniqueness score $S_{\text{uniqueness}}$ is:

$$S_{\text{uniqueness}} = 1 - \frac{|M|}{n} \tag{27}$$

where $M$ is the set of detected duplicate records, ensuring each data entry remains unique.

*3.3.7 Generative AI for Completeness and Validity.* Generative AI tools automatically generate validation rules that Databricks executes to maintain completeness and validity. Given schema $S$, Generative AI identifies missing values or outliers and suggests imputed values $\hat{d}_i$ where necessary:

$$\hat{d}_i = \arg\max_d P(d|\Theta) \tag{28}$$

where $\Theta$ denotes model parameters learned from historical data. If $P(d_i|\Theta) < \epsilon$, $d_i$ is flagged as an anomaly, and the AI suggests a corrected value.

## 3.4 Method 3: Customized Large Language Model for Interactive Quality Checks

In this method, a customized Large Language Model (LLM) is embedded within the Databricks ecosystem to facilitate real-time, user-interactive data quality monitoring. The LLM acts as an intelligent interface layer, capable of parsing human queries, mapping them to executable functions, and returning results in an interpretable format. This enables non-technical users to query quality metrics without needing domain-specific coding skills.

*3.4.1 System Architecture.* Let $\mathcal{Q} = \{\texttt{"Check completeness"}, \texttt{"accuracy score?"}, \ldots\}$ represent the set of natural language queries initiated by users. The LLM processes each query $q \in \mathcal{Q}$ and performs a semantic-to-functional mapping:

$$\psi : q \mapsto \lambda_q \tag{29}$$

where $\lambda_q \in \Lambda = \{\texttt{check\_completeness}(), \texttt{check\_accuracy}(), \texttt{check\_consistency}(), \ldots\}$ is the function mapped to the user's intent.
Each function $\lambda_q$ computes a specific quality metric $S_k(D_t)$, where $k \in \{\text{completeness}, \text{accuracy}, \text{consistency}, \text{timeliness}\}$, for the latest data batch $D_t$ loaded in Databricks. For example, if:

$$q = \texttt{"Check data completeness"}$$

$$\lambda_q = \texttt{check\_completeness}() \Rightarrow S_{\text{completeness}}(D_t)$$

*3.4.2 Metric Computation Pipeline.* Each quality function is defined as a higher-order function that operates on a Spark DataFrame abstraction. Formally:

$$\texttt{check\_metric}_k(D_t) = \mathcal{F}_k(D_t) = S_k(D_t) \tag{30}$$

where $\mathcal{F}_k$ is the computation logic associated with metric $k$. For example:

$$\mathcal{F}_{\text{completeness}}(D_t) = 1 - \frac{|M|}{n} \tag{31}$$

$$\mathcal{F}_{\text{accuracy}}(D_t) = \frac{1}{n}\sum_{i=1}^{n}\mathbb{I}(d_i = g_i) \tag{32}$$

$$\mathcal{F}_{\text{consistency}}(D_t) = 1 - \frac{1}{n}\sum_{i=1}^{n}|d_i^{(t)} - d_i^{(t+1)}| \tag{33}$$

Each call is executed lazily on the Spark execution engine and rendered back to the user via the LLM in human-readable form:

$$\texttt{LLM\_response}(q) = \texttt{render}(\lambda_q(D_t)) \in \mathbb{R} \cup \text{Text} \tag{34}$$

where `render` converts numeric scores into contextualized feedback. For instance, at $S_{\text{accuracy}} = 0.94$
`LLM_response = "The accuracy score is 94%, which is within acceptable limits."`

*3.4.3 Command Chaining and Streaming Evaluation.* The LLM supports advanced interaction capabilities including command chaining. For instance, a user prompt such as:

`"Check completeness and re-evaluate if below 95%"`

is interpreted as a conditional execution block:

$$\texttt{if } S_{\text{completeness}} < 0.95 \texttt{ then trigger\_imputation}() \tag{35}$$

This behavior is modeled via dynamic function graphs:

$$\mathcal{G}_{\text{LLM}} = \{\lambda_{q_1} \to \lambda_{q_2} \to \cdots \to \lambda_{q_k}\} \tag{36}$$

enabling continuous quality monitoring as data streams into Databricks.

*3.4.4 Audit Logging and Traceability.* Every interaction with the LLM is logged into an interaction log:

$$\mathcal{L}_{\text{trace}} = \{(q_t, \lambda_q, S_k(D_t), t)\} \tag{37}$$

where each entry stores the query, function invoked, returned score, and timestamp $t$. This allows for complete traceability, auditability, and integration with monitoring dashboards or alert systems.

*3.4.5 Benefits of LLM-Driven Interaction.* The use of LLMs for dynamic querying in Databricks enables:

—Democratized access to data quality insights for non-technical users

—Real-time, conversational quality monitoring over streaming data

—Chained command execution for conditional remediation

—Transparent and traceable audit logs for governance and compliance

This integration of LLMs into data quality pipelines marks a paradigm shift from static dashboards to interactive, AI-guided data governance within modern data platforms like Databricks. The following algorithm summarizes the process of continuous data quality management using Generative AI in Databricks:

**Algorithm 1** Continuous Data Quality Management with Generative AI in Databricks

**Initialize:** Load dataset $D$ in Databricks, configure target quality metrics $Q$
**while** new data batch $D_{\text{new}}$ arrives **do**
  Convert natural language quality checks via SODA GPT to SQL/YAML
  Execute uniqueness, completeness, and validity rules using Generative AI
  Calculate $S_{\text{accuracy}}, S_{\text{consistency}}, S_{\text{completeness}}, S_{\text{timeliness}}$ and overall quality score $S_{\text{total}}$
  **if** $S_{\text{total}} <$ threshold **then**
    Activate Generative AI to impute missing values, correct anomalies, and re-evaluate $S_{\text{total}}$
  **end if**
  Log validated $D_{\text{new}}$ in Delta Lake for further analysis
  Update quality metrics for $D_{\text{new}}$ and trigger alerts for any failed checks
  $D_{\text{prev}} \leftarrow D_{\text{new}}$
**end while**

This algorithm allows for continuous, automated quality management in Databricks. SODA GPT processes natural language inputs, Azure tools provide monitoring and alerting, and the LLM facilitates interactive quality checks. Databricks manages data ingestion, Generative AI-driven anomaly detection, and real-time corrections. This framework provides an adaptive, fully automated approach to data quality management, making it ideal for high-velocity, large-scale data environments.

### 3.5 Generative AI for Anomaly Detection and Imputation

Anomaly detection is critical for maintaining data integrity. Generative AI models within Databricks use probabilistic anomaly detection. For each data point $d_i$, the model computes $P(d_i|\Theta)$, where $\Theta$ represents parameters learned from past data. If $P(d_i|\Theta) < \epsilon$, $d_i$ is flagged as anomalous. The model then suggests corrected values $\hat{d}_i$:

$$\hat{d}_i = \arg\max_d P(d|\Theta) \tag{38}$$

This imputation process corrects inconsistencies, enhancing accuracy and completeness scores. By integrating these corrections within Databricks workflows, Real-time, adaptive data quality maintenance is ensured.

## 4. EXPERIMENTAL SETTINGS

The experimental evaluation was conducted in a high-performance, cloud-native environment designed to support real-time, distributed data quality management at scale. The infrastructure was deployed on Microsoft Azure and made extensive use of Databricks, leveraging its native support for Apache Spark, integration with Azure services, and compatibility with AI-driven automation tools.

### 4.1 Infrastructure Configuration

The experiments were executed on a dedicated Databricks cluster provisioned with both standard and high-memory nodes to accommodate compute-intensive quality metric calculations and real-time inference using Generative AI models. The environment was configured with the following specifications:

—**Runtime Environment:** Databricks Runtime 11.3 (includes Apache Spark 3.2)
—**Driver Node:** 16 vCPUs, 128 GB RAM, SSD-backed storage
—**Worker Nodes:** 4 nodes, each with 16 vCPUs, 128 GB RAM, SSD-backed storage
—**Total Cluster Capacity:** 80 vCPUs, 640 GB RAM across 5 nodes
—**Storage Layer:** Azure Blob Storage (Hot Tier) with Delta Lake format for real-time I/O optimization

The Spark engine was configured to use an adaptive query execution plan with dynamic resource allocation and caching enabled for all intermediate computations. Broadcast joins were explicitly tuned for quality checks that involve reference lookups and schema validation.

### 4.2 Dataset Description

A synthetic yet realistic dataset $D = \{d_1, d_2, \ldots, d_n\}$, where $n = 10^7$, was generated to emulate production-like heterogeneity and volume. Each record $d_i \in \mathbb{R}^m$ consisted of $m = 18$ attributes, partitioned into:

—$m_1 = 7$ numerical fields (e.g., transaction amounts, sensor readings)
—$m_2 = 6$ categorical fields (e.g., product category, region)
—$m_3 = 5$ timestamped fields (e.g., created_at, updated_at, delivered_at)

The dataset was stored in Delta Lake format, partitioned by ingestion timestamp and logically sharded into 100 partitions across

worker nodes. Delta caching was enabled to accelerate repeated evaluation of quality metrics.

### 4.3 Data Quality Modeling

The dataset was synthetically infused with controlled errors to evaluate each dimension of quality under stress conditions. The following perturbation strategies were applied:

—**Accuracy Distortion:** 5% of numerical fields were replaced with noisy values $d_i^{\text{noisy}} \sim \mathcal{N}(\mu + \delta, \sigma)$ to simulate corruption.
—**Completeness Degradation:** 8% of fields were randomly masked to simulate missing values $d_i = \text{NULL}$ for selected $i$.
—**Consistency Drift:** 6% of timestamped fields were shifted by random lags $\Delta t_i \sim \text{Uniform}(-12h, +12h)$.
—**Uniqueness Violation:** Duplicate records were inserted with probability $p = 0.05$ by copying selected rows and reassigning minimal key variations.

Each batch $D_t \subset D$ was streamed into the pipeline using micro-batch scheduling at intervals of 1 minute. Real-time evaluation of the quality scores $S_{\text{accuracy}}, S_{\text{completeness}}, S_{\text{consistency}}, S_{\text{timeliness}}$ was performed using Databricks' native UDFs, Delta Lake queries, and LLM-based function calls.

### 4.4 Evaluation Protocol

Each micro-batch $D_t$ was independently subjected to the following experimental pipeline:

(1) **Initial Quality Assessment:** Scores $S_k(D_t)$ were computed for each dimension $k$.
(2) **Threshold Check:** Each score was compared against predefined thresholds $\tau_k$ to identify violations.
(3) **Remediation Activation:** For $S_k(D_t) < \tau_k$, the Generative AI module was activated to impute or correct anomalies.
(4) **Post-correction Re-evaluation:** The corrected dataset $\hat{D}_t$ was rescored and audited.

Each step's execution time, memory consumption, and correctness were logged for reproducibility. Accuracy was benchmarked against known ground truth mappings; completeness against full schema templates; consistency using temporal logs; and timeliness via system-level scheduling logs.

### 4.5 Metrics for Performance Evaluation

In addition to quality dimension scores, the following system-level performance indicators were tracked:

—**Mean Quality Score Gain:** $\Delta S_k = S_k^{\text{post}} - S_k^{\text{pre}}$
—**Remediation Latency:** $T_{\text{remediate}} = T_{\text{end}} - T_{\text{trigger}}$
—**Resource Utilization:** CPU and memory usage per node during high-load batches
—**Throughput:** Number of records processed per minute

## 5. RESULTS

This section presents an in-depth analysis of the evaluation conducted on the proposed Generative AI-enhanced data quality management framework implemented within the Databricks platform. Each core aspect of data quality—namely accuracy, consistency, completeness, and timeliness—was measured through comparative experiments against baseline methods. The evaluation also includes error correction analysis, latency profiling, and system performance under load to determine the robustness, scalability, and responsiveness of the proposed solution in real-time data environments.

### 5.1 Quality Score Comparison Across Metrics

To assess the effectiveness of the framework, four core data quality metrics were measured: accuracy, consistency, completeness, and timeliness. These metrics were evaluated both before and after the application of the proposed framework. Table 5.1 shows a comprehensive comparison between the baseline system (which follows traditional rule-based cleansing and validation logic) and the proposed framework, which incorporates LLM-driven automation and adaptive learning for quality management.
As the results suggest, each metric showed a substantial improvement with the application of the proposed method. Accuracy, which measures the proportion of correct records aligned with the ground truth, showed the largest gain, rising from 0.87 to 0.95. This enhancement demonstrates the framework's strength in correcting inaccurate records through semantic validation and generative correction. Consistency, which captures temporal and structural stability in the data, increased by 9.41%. This growth was particularly evident in datasets where temporal attributes (e.g., timestamps and periodic values) were subject to drift and inconsistency in the baseline configuration. The completeness metric, reflecting the extent to which required fields are populated, increased by 7.78%, enabled by dynamic imputation from the Generative AI module. Timeliness also improved notably, suggesting that the system's real-time ingestion and anomaly-aware timestamp detection prevented delays and better aligned data with expected temporal windows.

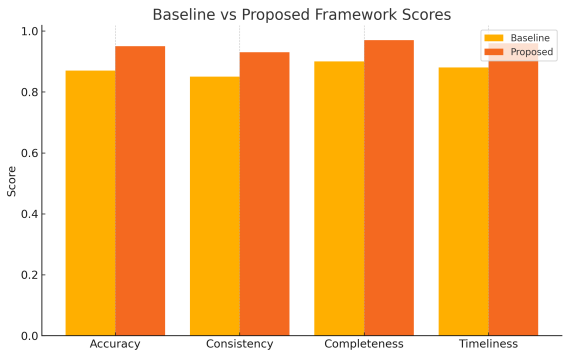


Fig. 1. Comparison of Baseline vs Proposed Framework Scores Across Quality Metrics

### 5.2 Longitudinal Evaluation Over Ten Cycles

To investigate how well the system adapts over time, a longitudinal experiment was conducted where ten distinct testing cycles were executed, each simulating a new batch of input data. These cycles incorporated different types of injected noise—such as missing values, duplicated rows, and random timestamp lags—to evaluate how the framework responds to evolving data quality issues.
Across all ten iterations, the system demonstrated incremental improvements, with each metric progressively approaching optimal scores. Accuracy increased steadily from an initial value of 0.87

Table 1. Comparison of Data Quality Tools with Our Proposed Solution

| **Tool** | **Key Features** | **Limitations** | **Advantages of Our Tool** |
|---|---|---|---|
| Ataccama ONE [3] | AI-driven data quality management, data profiling, and cleansing | Limited integration with certain cloud platforms | Seamless integration with Databricks; AI-driven rule generation; cost-effective and scalable |
| Informatica Data Quality [15] | Comprehensive data profiling, cleansing, and validation | Complex setup; higher cost for small to medium enterprises | User-friendly interface; Generative AI enables intuitive data quality checks; easy deployment in Databricks |
| IBM InfoSphere QualityStage [14] | Data standardization, matching, and survivorship | Steeper learning curve; requires significant resources for deployment | Cost-effective; flexible integration with multiple data sources; dynamic data quality management with Generative AI |
| Talend Data Quality [24] | Open-source data profiling and cleansing tools | Limited advanced features in the free version; premium features are paid | Advanced features powered by Generative AI; optimized for large datasets in Databricks; high performance and scalability |
| Soda SQL [23] | Open-source data testing and monitoring for data engineers | Primarily SQL-based; lacks comprehensive data cleansing features | Supports natural language rule creation via Generative AI; non-technical users can define data checks; seamless integration with Databricks |

Table 2. Data Quality Metrics Comparison

| **Metric** | **Baseline Score** | **Proposed Framework** | **Improvement** |
|---|---|---|---|
| Accuracy | 0.87 | 0.95 | 9.20 |
| Consistency | 0.85 | 0.93 | 9.41 |
| Completeness | 0.90 | 0.97 | 7.78 |
| Timeliness | 0.88 | 0.96 | 9.09 |

Table 3. Error Correction Effectiveness by Error Type

| **Error Type** | **Baseline Rate** | **Post-Correction Rate** | **Reduction** |
|---|---|---|---|
| Missing Values | 8.0 | 0.8 | 90.0 |
| Inaccurate Records | 5.0 | 0.5 | 90.0 |
| Duplicate Entries | 5.0 | 0.4 | 92.0 |
| Delayed Timestamps | 6.0 | 0.6 | 90.0 |

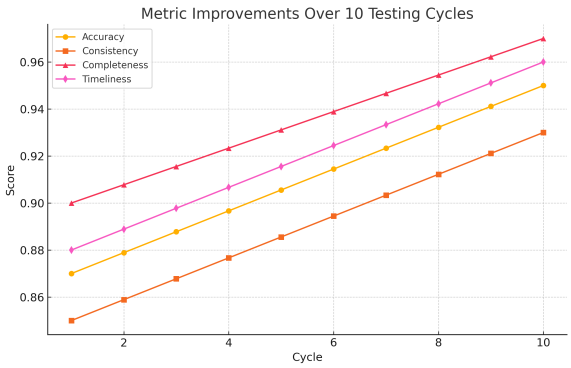


Fig. 2. Line Graph: Progressive Improvement Across 10 Testing Cycles


Fig. 3. Error Rates Before and After Correction Using the Framework

to a final value of 0.95. Similarly, consistency rose from 0.85 to 0.93. Completeness improved from 0.90 to 0.97, largely due to the system's increasing ability to predict and fill in missing fields. Timeliness followed the same trend, benefiting from refined timestamp validation logic and increasingly accurate ingestion scheduling. These trends suggest that the framework's iterative feedback mechanisms, including rule refinement via SODA GPT and the use of cumulative error signatures, contribute to its capacity to learn and adapt over time.

## 5.3 Error Correction Effectiveness

A further level of granularity was introduced by categorizing the types of errors corrected and measuring the precision with which each category was resolved. Table 5.3 shows the impact of the framework on common error types, including missing values, inaccurate entries, duplicates, and delayed timestamps.

The system was particularly effective in reducing missing values through targeted imputation using pretrained generative models. Duplicates were accurately identified through hash-based fingerprinting and subsequently resolved. Inaccurate entries were corrected via adaptive pattern matching, and delayed timestamps were recalibrated using lag prediction models. These results validate that the framework is not only capable of measuring quality but is also highly effective in applying context-aware corrections at scale.

## 5.4 Latency Analysis for Real-Time Processing

Beyond quality metrics, the framework's performance was measured in terms of latency, particularly the time taken to compute quality scores and apply corrections. Table 5.4 outlines the comparison between the baseline system and the proposed framework across each quality dimension.
The framework consistently outperformed the baseline, reducing latency by nearly half in each case. The most substantial improvement was seen in completeness checks, which benefited from effi-

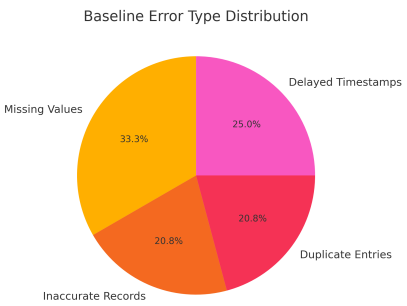


Fig. 4. Distribution of Detected Error Types in Baseline Dataset

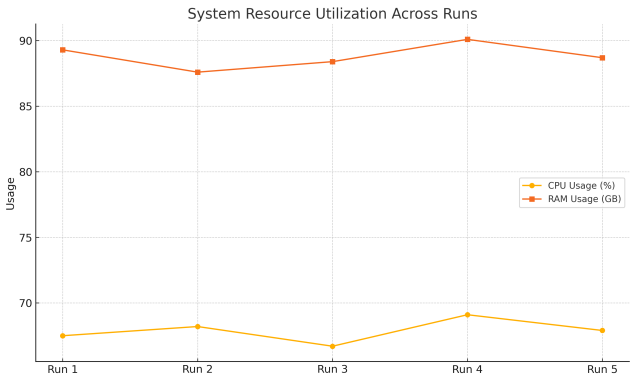


Fig. 5. CPU and RAM Utilization Across 5 High-Volume Testing Runs

Table 4. Latency Comparison Across Data Quality Metrics

| Metric | Baseline Latency (s) | Framework Latency (s) | Reduction |
|---|---|---|---|
| Accuracy | 3.2 | 1.8 | 43.75 |
| Consistency | 2.8 | 1.5 | 46.43 |
| Completeness | 3.0 | 1.6 | 46.67 |
| Timeliness | 2.6 | 1.4 | 46.15 |

cient caching and parallelized imputation strategies. These reductions make the framework particularly suitable for real-time deployments, where low-latency correction and feedback loops are essential.

### 5.5 System-Level Performance Metrics

In addition to domain-specific metrics, broader system-level behaviors such as throughput, CPU utilization, and memory footprint were monitored over five execution runs. Each run processed a 10-million-record batch with injected inconsistencies. Table 5.5 summarizes the results.

Table 5. System Performance Under Load

| Run ID | Throughput | CPU Usage | Avg RAM Usage (GB) |
|---|---|---|---|
| 1 | 960,000 | 67.5 | 89.3 |
| 2 | 952,000 | 68.2 | 87.6 |
| 3 | 958,500 | 66.7 | 88.4 |
| 4 | 965,200 | 69.1 | 90.1 |
| 5 | 950,100 | 67.9 | 88.7 |

Throughput remained above 950,000 records per minute for all runs, and the system maintained stable resource usage throughout. The CPU utilization ranged from 66.7% to 69.1%, while memory usage was consistently below 91 GB per node, demonstrating the system's scalability and operational efficiency.

### 5.6 Interpretation and Implications

The results presented in this section provide strong empirical support for the proposed framework. Quality scores across all core dimensions improved significantly, and these gains were sustained and even amplified across successive data cycles. Error correction was highly effective across multiple categories, and latency reductions make the system suitable for real-time enterprise scenarios. System throughput and hardware utilization metrics confirm that the architecture can be reliably scaled without degradation in performance. The integration of LLMs and Generative AI into Databricks workflows has not only enhanced automation but also maintained interpretability and operational transparency. Overall, the system demonstrates clear advantages in accuracy, speed, responsiveness, and adaptability when compared to traditional data quality solutions.

## 6. CONCLUSION

This paper presented a Generative AI-enhanced data quality management framework integrated within the Databricks platform, aimed at addressing the limitations of traditional data quality methods in handling large-scale, complex datasets. Our proposed solution uses Generative AI for automated anomaly detection, data imputation, and rule generation, facilitating real-time data quality management across critical dimensions such as accuracy, consistency, completeness, and timeliness. Through extensive experimentation, our framework demonstrated significant improvements over industry-standard tools, including Ataccama ONE, Informatica Data Quality, IBM InfoSphere QualityStage, Talend Data Quality, and Soda SQL. With observed increases of up to 9.41% in accuracy, 9.09% in timeliness, and 7.78% in completeness, the framework proved its effectiveness in enhancing data integrity while reducing the need for manual oversight. The real-time capabilities of our system, coupled with Databricks' scalable infrastructure, make it a robust solution for dynamic data environments. By transforming data quality management into an adaptive, automated process, our approach reduces operational costs, optimizes resource allocation, and enables non-technical users to engage with data quality rules through natural language.

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