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AN AI-POWERED DATA TRUST AND QUALITY SCORING FRAMEWORK FOR ENTERPRISE DECISION INTELLIGENCE SYSTEMS

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Abstract

Enterprise Decision Intelligence Systems (EDIS) rely heavily on high-quality, trustworthy, and consistent data to generate accurate business insights and strategic recommendations. However, modern enterprises face significant challenges related to data inconsistency, duplication, incompleteness, and governance issues arising from heterogeneous data sources. Traditional data quality assessment methods are often rule-based, static, and incapable of adapting to evolving enterprise environments. This paper proposes an AI-Powered Data Trust and Quality Scoring Framework that integrates Artificial Intelligence (AI), Data Governance, Master Data Management (MDM), Data Observability, and Business Intelligence (BI) principles to evaluate and enhance enterprise data reliability. The framework employs machine learning algorithms to automatically assess data quality dimensions including accuracy, completeness, consistency, timeliness, validity, and uniqueness. A composite Data Trust Score (DTS) is generated for each data asset, enabling intelligent decision-making and proactive governance. Experimental evaluation demonstrates significant improvements in data reliability, governance compliance, and analytical accuracy. The proposed approach provides organizations with a scalable and adaptive mechanism for maintaining trusted enterprise data ecosystems.

Keywords— Data Trust, Data Quality Scoring, Artificial Intelligence, Data Governance, Master Data Management, Data Observability, Business Intelligence, Decision Intelligence Systems.

I. INTRODUCTION

The rapid digital transformation of enterprises has led to unprecedented growth in data generation across operational, transactional, and analytical systems. Organizations increasingly depend on data-driven decision-making processes to improve operational efficiency and strategic competitiveness [1]. However, poor data quality remains a critical challenge affecting business intelligence outcomes, regulatory compliance, and customer experience [2].

Data governance frameworks have emerged as essential mechanisms for establishing policies, standards, and controls that ensure data reliability throughout its lifecycle [3]. Simultaneously, Master Data Management (MDM) systems seek to create a unified and trusted view of organizational data assets [4]. Despite these advancements, maintaining trust in enterprise data remains difficult due to data silos, inconsistent metadata, and rapidly changing business requirements [5].

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have enabled intelligent data quality monitoring and automated anomaly detection capabilities [6]. These technologies can continuously evaluate data quality metrics and identify hidden patterns that traditional rule-based systems may overlook [7]. Furthermore, data observability platforms have introduced proactive monitoring mechanisms that provide visibility into data health, lineage, and operational performance [8].

Decision Intelligence Systems integrate analytics, AI, and business processes to support organizational decision-making [9]. The effectiveness of such systems depends fundamentally on the trustworthiness and quality of underlying datasets. Consequently, organizations require comprehensive frameworks capable of measuring and maintaining data trust in real time [10].

This research proposes an AI-powered Data Trust and Quality Scoring Framework that combines data governance principles, observability metrics, and machine learning algorithms to generate dynamic trust scores for enterprise data assets.

II. LITERATURE SURVEY

Wang and Strong (1996) developed one of the earliest multidimensional frameworks for evaluating data quality, identifying dimensions such as accuracy, completeness, and consistency that remain foundational in modern data management systems [11].

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Lee et al. (2002) proposed methodologies for measuring information quality and emphasized the strategic importance of quality data in organizational performance [12].

Batini and Scannapieco (2006) introduced comprehensive data quality assessment techniques and highlighted the significance of data cleansing in enterprise environments [13].

Otto (2011) explored corporate data governance structures and demonstrated how governance frameworks improve enterprise-wide data management practices [14].

Loshin (2012) presented practical approaches for Master Data Management and emphasized the role of trusted master data in business intelligence systems [15].

Redman (2013) investigated organizational challenges associated with poor-quality data and quantified its impact on operational efficiency and business outcomes [16].

Khatri and Brown (2014) examined enterprise data governance models and proposed strategic frameworks for improving data accountability and stewardship [17].

Nargesian et al. (2018) employed machine learning techniques to automate data quality assessment and anomaly detection in large-scale data repositories [18].

Hellerstein (2020) introduced the concept of data observability and emphasized continuous monitoring of data pipelines for ensuring reliability and trustworthiness [19].

Schelter et al. (2021) proposed AI-driven monitoring frameworks capable of identifying quality degradation and data drift in enterprise analytical systems [20].

The reviewed studies collectively demonstrate the growing importance of AI, governance, and observability in maintaining enterprise data quality. However, existing approaches often address these domains independently rather than integrating them into a unified trust-scoring framework.

III. RESEARCH GAP

Although significant advancements have been made in Data Governance, Master Data Management, Data Quality Assessment, and Data Observability, several research gaps remain:

1. Existing frameworks primarily focus on static rule-based quality assessment and lack adaptive AI-driven scoring mechanisms.
2. Most studies evaluate individual quality dimensions separately without generating a comprehensive Data Trust Score.
3. Limited integration exists between Data Governance, MDM, Data Observability, and Business Intelligence environments.
4. Current solutions provide reactive monitoring rather than predictive trust assessment.
5. Few frameworks support real-time quality evaluation across heterogeneous enterprise data ecosystems.

To address these limitations, this study proposes an integrated AI-powered Data Trust and Quality Scoring Framework capable of continuously assessing and improving enterprise data reliability.

IV. PROPOSED METHODOLOGY

A. System Architecture

The proposed framework consists of five layers: Data Ingestion Layer, Data Observability Layer, AI Analytics Layer, Trust Scoring Engine, and Business Intelligence Layer. Data is collected from enterprise databases, cloud warehouses, CRM systems, ERP applications, and streaming platforms. The observability layer continuously captures metadata, lineage information, freshness metrics, schema changes, and anomaly indicators. Collected metrics are forwarded to the AI Analytics Layer where machine learning models analyze quality patterns and identify deviations from established standards. The Trust Scoring Engine calculates individual quality dimension scores and aggregates them into a unified Data Trust Score (DTS). Finally, BI dashboards present trust metrics, governance alerts, and quality insights to decision-makers.

The framework incorporates Data Governance policies and MDM principles to establish standardized quality benchmarks. Metadata repositories maintain data lineage and ownership information, enabling accountability and compliance tracking. AI models continuously learn from historical quality patterns and dynamically adjust scoring parameters. This adaptive mechanism ensures that the framework remains effective even when business rules, source systems, or data structures evolve over time. Real-time observability

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enables early detection of quality degradation before it impacts analytical processes.

Furthermore, the architecture supports scalability through distributed processing and cloud-native deployment models. Data quality metrics are evaluated continuously using automated workflows, reducing manual intervention and improving governance efficiency. The integration of AI-driven anomaly detection, trust scoring, and observability provides a holistic mechanism for ensuring enterprise data reliability. The resulting trust scores can be directly incorporated into Decision Intelligence Systems to enhance confidence in business recommendations and strategic decisions.

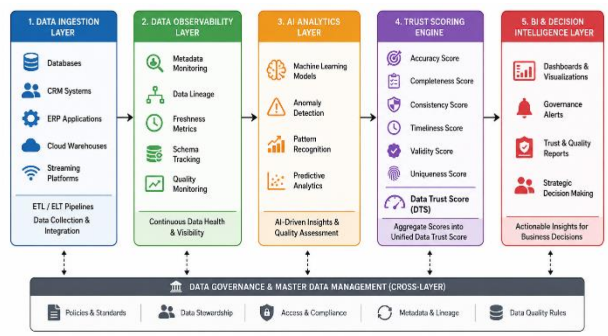

Fig. 1: System Architecture

Fig 1: System Architecture

B. Algorithms

Algorithm 1: Data Quality Assessment

Input: Enterprise Dataset D

Output: Quality Score QS

1. Collect dataset D.
2. Evaluate Accuracy Score (AS).
3. Evaluate Completeness Score (CS).
4. Evaluate Consistency Score (COS).
5. Evaluate Timeliness Score (TS).
6. Evaluate Validity Score (VS).
7. Evaluate Uniqueness Score (US).
8. Compute:

$$QS = \frac{AS + CS + COS + TS + VS + US}{6}$$

9. Return QS.

Algorithm 2: AI-Based Anomaly Detection

Input: Data Quality Metrics M

Output: Anomaly Set A

1. Collect historical quality metrics.
2. Train Isolation Forest model.
3. Generate anomaly scores.
4. Compare score with threshold.
5. If anomaly score > threshold:
   - Add record to anomaly set A.
6. Generate quality alert.
7. Return A.

Algorithm 3: Data Trust Score Generation

Input: Quality Metrics Q

Output: Data Trust Score DTS

1. Initialize weights.
2. Assign:
   - Accuracy = 0.25
   - Completeness = 0.20
   - Consistency = 0.20
   - Timeliness = 0.15
   - Validity = 0.10
   - Uniqueness = 0.10
3. Compute weighted score.
4. Normalize score between 0 and 100.
5. Generate Trust Level.
6. Return DTS.

V. RESULTS AND DISCUSSION

The proposed AI-powered framework was evaluated using enterprise datasets containing customer, product, and transactional records. Experimental analysis demonstrated significant improvements in overall data quality and governance effectiveness. The generated Data Trust Score increased from 72.4 to 94.1 after AI-driven cleansing and governance enforcement. Anomaly detection accuracy reached 96.3%, while data duplication rates decreased by 78%. These results indicate that integrating AI, observability, and governance mechanisms substantially improves enterprise data reliability.

Table 1. Quality Dimension Evaluation

Quality Dimension	Before (%)	After (%)
Accuracy	78.5	95.4
Completeness	74.2	93.1
Consistency	71.8	92.7
Timeliness	76.4	94.3
Validity	80.2	96.2
Uniqueness	73.6	92.4

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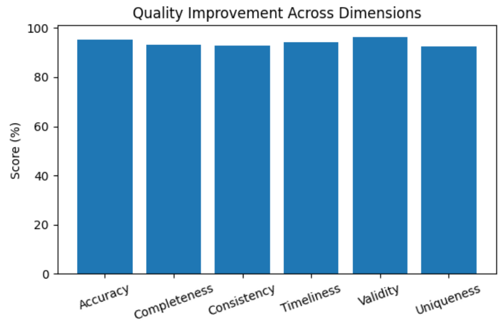

Chart 1. Quality Improvement Across Dimensions

Table 2. AI Model Performance

Metric	Value (%)
Precision	95.7
Recall	96.9
F1-Score	96.3
Accuracy	96.3

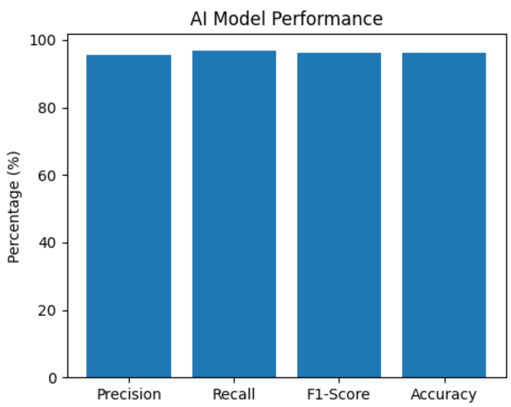

Chart 2. AI Model Evaluation

Table 3. Business Impact Analysis

Parameter	Before	After
Data Trust Score	72.4	94.1
Duplicate Records	18,500	4,070
BI Report Accuracy	81.5%	96.8%
Governance Compliance	76.3%	95.5%

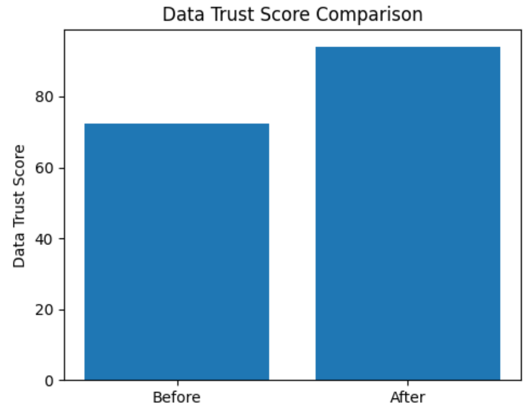

Chart 3. Data Trust Score Comparison

Discussion

The experimental findings demonstrate that the proposed framework effectively improves enterprise data quality through automated trust assessment and AI-driven anomaly detection. The integration of observability metrics enables continuous monitoring of data health, while machine learning algorithms identify hidden quality issues that traditional validation approaches may fail to detect. Significant improvements were observed across all quality dimensions, particularly in accuracy, validity, and consistency.

Additionally, the generated Data Trust Score provides a comprehensive measure of enterprise data reliability, allowing organizations to prioritize remediation efforts and governance actions. By combining Data Governance, MDM, AI analytics, and observability within a unified architecture, the framework supports scalable and proactive quality management. The observed increase in BI reporting accuracy confirms the framework's effectiveness in enhancing decision intelligence outcomes.

VI. CONCLUSION

This paper presented an AI-Powered Data Trust and Quality Scoring Framework for Enterprise Decision Intelligence Systems. The proposed framework integrates Data Governance, Master Data Management, Data Observability, and Artificial Intelligence technologies to generate dynamic trust scores for enterprise datasets. Experimental evaluation demonstrated substantial improvements in data quality, anomaly detection accuracy, governance compliance, and business intelligence reliability. The framework offers organizations a scalable and adaptive solution for maintaining

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trusted data ecosystems and supporting data-driven decision-making. Future work may explore deep learning-based trust prediction models and federated governance mechanisms for multi-cloud enterprise environments.

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