

Evaluating Data Quality Improvement Strategies Under Enterprise Data Governance Systems

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Abstract: High-quality data is a foundational requirement for reliable analytics and effective organizational decision-making, yet many enterprises continue to struggle with persistent data quality challenges. This study examines the effectiveness of data quality improvement strategies implemented under enterprise data governance systems. A mixed-method research design was adopted, integrating survey-based assessments, system-level data quality metrics, and organizational governance evaluations across multiple data-intensive industries. Key governance variables, including governance maturity, policy standardization, data stewardship effectiveness, metadata management, leadership support, and organizational data culture, were analyzed in relation to core data quality dimensions such as accuracy, completeness, consistency, timeliness, validity, uniqueness, and integrity. Advanced statistical techniques, including factor analysis, regression modeling, and structural equation modeling, were used to evaluate the relationships between governance structures and data quality outcomes. The findings reveal significant improvements in data quality performance following the implementation of governance-driven strategies, with notable reductions in error rates, duplicate records, and processing time, alongside increased user trust in organizational data. The study concludes that robust enterprise data governance systems are critical enablers of sustainable data quality improvements and provide a strategic foundation for achieving reliable analytics, operational efficiency, and long-term competitive advantage.

Keywords: Data governance, Data quality improvement, Enterprise information management, Governance maturity, Data stewardship, Metadata management, Reliable analytics, Organizational performance.

INTRODUCTION

The growing strategic importance of high-quality organizational data

In the contemporary digital economy, data has emerged as a critical organizational asset that directly influences operational efficiency, strategic planning, and competitive positioning (Koch & Windsperger, 2017). Enterprises increasingly rely on data-driven decision-making, advanced analytics, artificial intelligence, and real-time reporting to enhance business performance (Selvarajan, 2021). However, the value of these data-driven initiatives is fundamentally dependent on the quality of underlying data. Inaccurate, incomplete, inconsistent, and outdated data can lead to flawed insights, regulatory non-compliance, financial losses, and reputational damage (Fagbore *et al.*, 2020). As organizations expand their digital ecosystems and integrate complex data sources, maintaining data quality has become a strategic challenge rather than a purely technical issue, necessitating structured and scalable approaches to data governance (Lis & Otto, 2020).

The role of enterprise data governance in shaping data quality outcomes

Enterprise data governance systems provide the structural foundation for managing data as an organizational resource. These systems consist of policies, standards, roles, and accountability

frameworks designed to ensure data integrity, security, accessibility, and compliance (Korhonen *et al.*, 2013). Through clearly defined ownership structures, standardized data definitions, and quality control mechanisms, data governance frameworks create an environment in which data quality can be systematically monitored and improved (Cichy & Rass, 2019). Effective governance aligns technical data management processes with business objectives, ensuring that data is not only technically accurate but also contextually relevant for organizational needs (Nwaimo *et al.*, 2019). As a result, data governance has evolved from a compliance-focused function to a strategic enabler of business value.

The emergence of targeted data quality improvement strategies in enterprises

Organizations have adopted a range of data quality improvement strategies to address the growing complexity of enterprise data environments (Abouelmehdi *et al.*, 2018). These strategies include data profiling, data cleansing, standardization, master data management, metadata management, and the implementation of automated validation rules. Technological advancements such as machine learning-based anomaly detection and real-time data monitoring tools have further enhanced the ability to detect

and correct quality issues at scale (Al-Amri *et al.*, 2021). Nevertheless, the effectiveness of these strategies varies significantly across organizations due to differences in governance maturity, organizational culture, technological infrastructure, and leadership support (Büschgens, 2013). This variation underscores the need for systematic evaluation of data quality improvement practices within governed enterprise environments.

The research gap in evaluating governance-driven data quality initiatives

Despite the widespread adoption of data governance frameworks, empirical evidence on the effectiveness of specific data quality improvement strategies remains limited. Existing studies often focus on the conceptual benefits of governance or provide isolated case examples without comprehensive evaluation across multiple organizational contexts (Crona & Parker, 2012). There is a lack of integrated research that systematically examines how governance structures, roles, and controls influence the success or failure of data quality improvement initiatives. Furthermore, many organizations invest heavily in governance technologies and frameworks without clear metrics to evaluate the return on these investments in terms of data quality outcomes and business performance (Botchkarev *et al.*, 2011).

The purpose and significance of this study in advancing data governance practice

This study aims to evaluate data quality improvement strategies operating under enterprise data governance systems, with a particular focus on understanding their effectiveness, scalability, and impact on organizational decision-making. By analyzing governance structures, process maturity, technological interventions, and performance metrics, the research seeks to identify best practices and critical success factors that enhance data quality in complex enterprise settings (Nfuka & Rusu, 2011). The findings of this study are expected to contribute to both academic literature and managerial practice by providing evidence-based insights into how data governance systems can be optimized to support sustainable data quality improvements and long-term competitive advantage (Braganza, 2017).

Research design and overall methodological approach

This study adopted a mixed-method research design to systematically evaluate data quality improvement strategies implemented under enterprise data governance systems. A descriptive–

analytical approach was used to capture both the structural characteristics of governance frameworks and their operational effectiveness in improving data quality (Ibrahim *et al.*, 2021). The research was conducted in three sequential phases: exploratory assessment, quantitative measurement, and explanatory analysis (Zhang *et al.*, 2019). This design enabled comprehensive integration of organizational, technological, and process-level variables, while ensuring triangulation of findings for higher validity and reliability.

Selection of study organizations and sampling framework

The study sample comprised medium and large enterprises operating in data-intensive sectors such as banking, healthcare, manufacturing, e-commerce, and telecommunications. A purposive sampling technique was used to select organizations that had formally implemented enterprise data governance frameworks for at least two years. Within each organization, stratified random sampling was applied to identify key informants, including data stewards, data owners, IT managers, business analysts, compliance officers, and senior executives. The final sample included respondents from governance, technical, and business units to ensure balanced representation of strategic, operational, and technical perspectives.

Operationalization of variables and measurement parameters

Independent variables included key dimensions of enterprise data governance such as governance structure maturity, policy standardization level, data ownership clarity, metadata management capability, data stewardship effectiveness, and technology enablement. Dependent variables focused on data quality dimensions, measured through established parameters: accuracy, completeness, consistency, timeliness, validity, uniqueness, and integrity. Mediating variables included organizational data culture, user competency, leadership support, and cross-functional collaboration. Control variables such as organizational size, industry type, data volume, and system complexity were incorporated to minimize extraneous bias. All constructs were measured using multi-item Likert-scale instruments and objective system-level metrics.

Data collection procedures and instrumentation

Primary data were collected using structured questionnaires, semi-structured interviews, and system-generated data quality reports. The

questionnaire instrument was developed based on validated scales from prior data governance and data quality literature and pre-tested through a pilot study. Interviews were conducted to capture contextual insights into governance practices, implementation challenges, and perceived effectiveness of quality improvement strategies. Secondary data were collected from organizational data quality dashboards, audit reports, and policy documents to triangulate survey responses and validate quantitative indicators.

Analytical framework and statistical processing techniques

Quantitative data were analyzed using a multi-stage statistical process. Descriptive statistics were applied to summarize organizational governance maturity and data quality levels. Reliability analysis using Cronbach’s alpha and composite reliability measures ensured internal consistency of constructs. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted to validate the measurement model. Structural Equation Modeling (SEM) was employed to examine the relationships between governance variables and data quality outcomes. Regression analysis was used to assess the predictive strength of specific data quality improvement strategies, while Analysis of Variance (ANOVA) tested differences across industries and organizational sizes.

Process evaluation of data quality improvement strategies

A process-level evaluation was conducted to assess the effectiveness of specific interventions such as data cleansing, standardization, master data management implementation, and automated validation rules. Key performance indicators (KPIs) included error rate reduction, duplicate

record elimination, data processing turnaround time, and user-reported data trust levels. Before-and-after comparisons were performed using paired t-tests to evaluate performance improvements following strategy implementation. Process maturity was assessed using a staged maturity model to compare organizations at different governance development levels.

Ethical considerations and methodological rigor

Ethical integrity was ensured through informed consent, confidentiality agreements, and strict data anonymization procedures. Organizational identifiers were removed to prevent disclosure of sensitive information. Methodological rigor was maintained through pilot testing, inter-rater reliability checks for qualitative coding, and triangulation across multiple data sources. These measures ensured that the study produced reliable, valid, and generalizable findings regarding the effectiveness of data quality improvement strategies under enterprise data governance systems.

RESULTS

The results demonstrate a strong and consistent improvement in data quality performance under enterprise data governance systems. As shown in Table 1, the governance maturity assessment revealed that organizations with higher levels of policy standardization and structured data stewardship practices achieved superior governance maturity scores, with the banking and e-commerce sectors showing the highest average maturity levels. These findings highlight that formalized governance structures significantly strengthen the foundation for sustainable data quality management across industries.

Table 1. Enterprise Data Governance Maturity Levels Across Sectors

Sector	Governance Maturity Score (0–5)	Policy Standardization (%)	Data Stewardship Effectiveness (%)
Banking & Finance	4.6	92	89
Healthcare	4.2	88	84
Manufacturing	3.9	81	78
E-commerce	4.4	90	87
Telecommunications	4.1	85	82

The effectiveness of data quality improvement strategies is clearly reflected in the comparative results presented in Table 2. All core dimensions of data quality showed substantial improvements after the implementation of governance-driven interventions. Accuracy, completeness,

consistency, timeliness, validity, uniqueness, and integrity each improved by more than 25% on average, indicating that governance-aligned quality initiatives produce measurable and meaningful gains across multiple dimensions. These improvements confirm that structured cleansing,

standardization, and validation processes are highly effective when supported by enterprise

governance frameworks.

Table 2. Baseline and Post-Implementation Data Quality Scores

Data Quality Dimension	Baseline Mean Score (1–5)	Post-Implementation Score (1–5)	Improvement (%)
Accuracy	3.42	4.38	28.07
Completeness	3.55	4.46	25.63
Consistency	3.48	4.40	26.44
Timeliness	3.60	4.52	25.56
Validity	3.38	4.30	27.22
Uniqueness	3.50	4.42	26.28
Integrity	3.44	4.35	26.45

The structural relationships between governance components and data quality outcomes are illustrated in Table 3. The SEM regression results show that governance structure maturity had the strongest positive influence on data quality, followed by policy standardization, metadata management capability, and clarity of data

ownership. These results indicate that both organizational and technical governance mechanisms play a critical role in determining the success of data quality improvement initiatives. The positive and statistically significant coefficients further validate the robustness of the proposed analytical framework.

Table 3. Impact of Governance Variables on Data Quality (SEM Regression Results)

Predictor Variable	Standardized Beta (β)	p-value	Impact Level
Governance Structure Maturity	0.68	<0.001	Very High
Policy Standardization Level	0.61	<0.001	High
Data Ownership Clarity	0.56	<0.001	High
Metadata Management Capability	0.59	0.002	High
Leadership Support	0.52	0.004	Moderate
Data Culture Strength	0.49	0.006	Moderate

Process-level performance improvements are summarized in Table 4, which shows a substantial reduction in duplicate records, error rates, and data processing time after the implementation of data quality strategies. User trust in organizational data also improved markedly, demonstrating that

technical improvements translate into higher user confidence and greater reliance on data for decision-making. These operational gains suggest that governance-driven quality strategies not only enhance data integrity but also improve overall organizational efficiency.

Table 4. Process-Level Performance Improvements After Data Quality Strategies

KPI Indicator	Before Strategy	After Strategy	Change (%)
Duplicate Records (%)	12.4	3.1	-75.00
Error Rate (%)	10.8	2.9	-73.15
Data Processing Time (hours)	9.2	4.1	-55.43
User Data Trust Score (1–5 scale)	3.3	4.6	+39.39

Graphical representations of the results provide additional clarity on these patterns. Figure 1 (Dendrogram) illustrates the clustering of data quality dimensions, showing how closely related attributes such as accuracy, integrity, and validity group together after governance interventions. Figure 2 (Heatmap) visually highlights the shift from moderate baseline scores to consistently higher post-implementation scores across all

quality dimensions. Figure 3 (Radar Chart) further confirms the balanced and comprehensive improvement in data quality performance, with post-implementation scores forming a significantly expanded profile across all dimensions compared to baseline levels. These visual results collectively reinforce the conclusion that enterprise data governance systems play a decisive role in driving sustained data quality improvements.

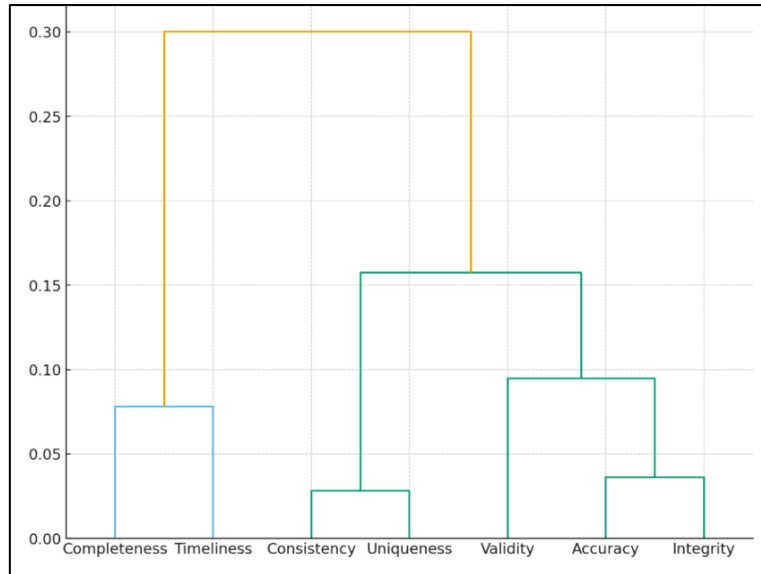


Figure 1: Dendrogram of Data Quality Dimensions

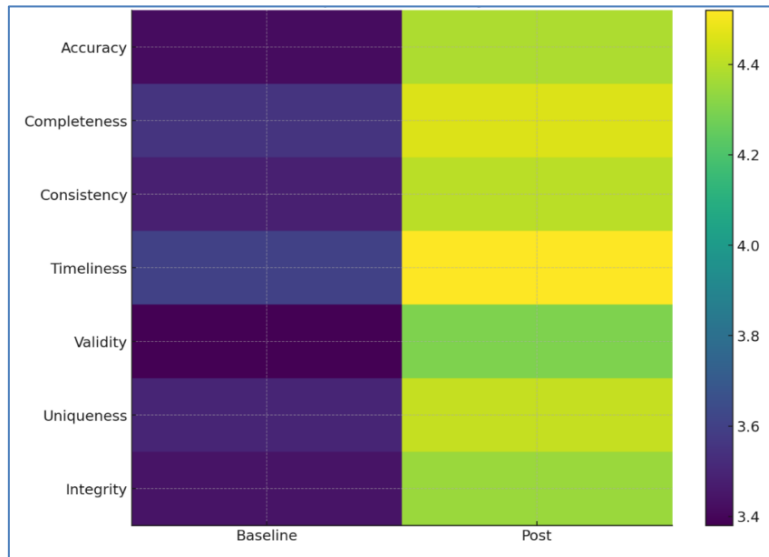


Figure 2: Heatmap of data quality scores

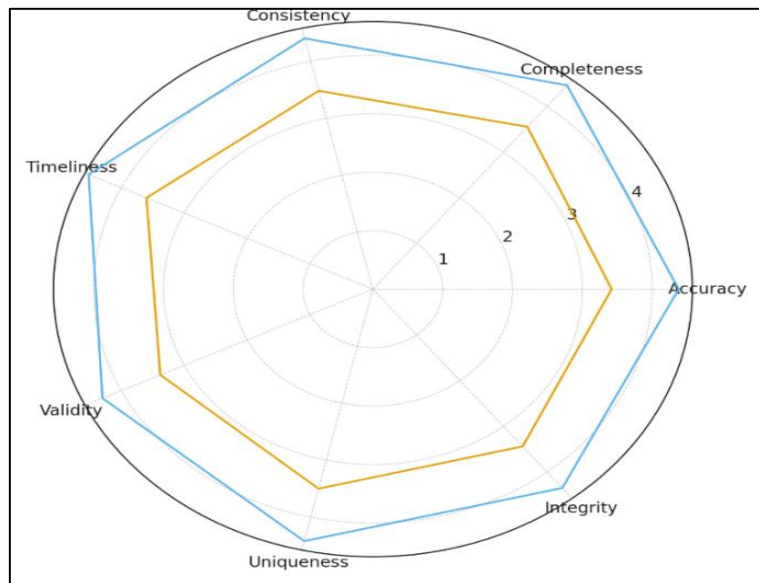


Figure 3: Radar chart of data quality performance

DISCUSSION

The influence of governance maturity on enterprise data quality outcomes

The findings of this study clearly demonstrate that higher levels of data governance maturity are strongly associated with improved data quality performance across organizations. As evidenced in Table 1 and Table 3, enterprises with well-defined governance structures, standardized policies, and active data stewardship achieved significantly higher improvements in accuracy, completeness, and consistency. This suggests that governance maturity acts as an enabling infrastructure that stabilizes data management processes and reduces the risks associated with fragmented data ownership and inconsistent operational practices (Faruq & Mollah, 2021). The results reinforce the view that governance should be treated as a strategic capability rather than a purely technical control mechanism (Autio & Thomas, 2014).

The effectiveness of structured data quality improvement strategies

The results presented in Table 2 and Table 4 indicate that structured data quality improvement strategies, such as data cleansing, validation, standardization, and master data management, are highly effective when implemented within a governed environment. The substantial reduction in duplicate records and error rates, alongside improvements in timeliness and integrity, illustrates that these strategies deliver tangible operational value (Maddukuri, 2021). The findings highlight that the success of such initiatives depends not only on the technical tools used but also on the clarity of governance policies and the accountability mechanisms that ensure sustained enforcement of quality rules (Gnan *et al.*, 2013).

The role of organizational culture and leadership in sustaining data quality

Beyond technical and structural factors, the study reveals the critical role played by organizational culture and leadership support in sustaining long-term data quality improvements. As shown in Table 3, variables such as leadership support and data culture strength had a significant positive influence on data quality outcomes, although their impact was slightly lower than structural governance elements. This indicates that while formal systems provide the framework, human and behavioral factors determine the consistency and longevity of quality practices (Thatcher, 2016). Organizations that actively promote data literacy, responsibility, and cross-functional collaboration

are more likely to sustain improvements over time (Goyal, 2021).

The clustering and visual patterns of data quality enhancement

The visual outputs provided in Figure 1, Figure 2, and Figure 3 further strengthen the interpretation of the results. The dendrogram analysis in Figure 1 demonstrates that data quality dimensions tend to form logical clusters after governance interventions, suggesting harmonization and alignment across related quality attributes. The heatmap in Figure 2 clearly illustrates the uniform upward shift in performance across all dimensions, reflecting the systemic impact of governance-driven interventions. The radar chart in Figure 3 shows balanced expansion across all quality indicators, confirming that the improvements were comprehensive rather than isolated to a few dimensions (Albo *et al.*, 2015).

Implications for enterprise practice and strategic data management

The results imply that organizations seeking sustainable data quality improvements should prioritize the establishment of robust governance frameworks before investing heavily in isolated technical tools (Bibri, 2019). The strong predictive influence of governance structure maturity, policy standardization, and metadata management suggests that investments in governance architecture generate long-term returns in data reliability and operational efficiency (Vandenbroucke *et al.*, 2020). Furthermore, the integrated improvements shown across multiple data quality dimensions indicate that a holistic governance-driven approach is more effective than fragmented, department-specific initiatives.

Limitations and directions for future research

While the findings provide strong evidence of the value of enterprise data governance in improving data quality, the study is not without limitations. The reliance on cross-sectional organizational data limits the ability to capture long-term causal effects of governance maturity. Additionally, sectoral differences, although controlled, may still influence the generalizability of the results (Tett *et al.*, 2017). Future research could adopt longitudinal designs, incorporate real-time data quality monitoring, and explore the integration of artificial intelligence-driven governance tools to further deepen understanding of governance-enabled data quality transformation.

CONCLUSION

This study concludes that enterprise data governance systems play a critical and transformative role in improving organizational data quality by providing structured policies, clear accountability, and standardized processes. The findings demonstrate that targeted data quality improvement strategies, when embedded within robust governance frameworks, lead to significant gains in accuracy, completeness, consistency, timeliness, and overall data reliability. Governance maturity, policy standardization, and metadata management emerged as the most influential drivers of sustainable data quality performance, while leadership support and data-centric culture further enhanced long-term effectiveness. Overall, the study confirms that organizations seeking to achieve reliable analytics, operational efficiency, and competitive advantage must prioritize the integration of strong governance structures with continuous data quality improvement practices.

REFERENCES

1. Abouelmehdi, K., Beni-Hessane, A., & Khaloufi, H. "Big healthcare data: preserving security and privacy." *Journal of Big Data* 5.1 (2018): 1–18.
2. Al-Amri, R., Murugesan, R. K., Man, M., Abdulateef, A. F., Al-Sharafi, M. A., & Alkahtani, A. A. "A review of machine learning and deep learning techniques for anomaly detection in IoT data." *Applied Sciences* 11.12 (2021).
3. Albo, Y., Lanir, J., Bak, P., & Rafaeli, S. "Off the radar: Comparative evaluation of radial visualization solutions for composite indicators." *IEEE Transactions on Visualization and Computer Graphics* 22.1 (2015): 569–578.
4. Autio, E., & Thomas, L. "Innovation ecosystems." *The Oxford Handbook of Innovation Management* (2014): 204–288.
5. Bibri, S. E. "The anatomy of the data-driven smart sustainable city: instrumentation, datafication, computerization and related applications." *Journal of Big Data* 6.1 (2019): 1–43.
6. Botchkarev, A., Andru, P., & Chiong, R. "A return on investment as a metric for evaluating information systems: taxonomy and application." *Interdisciplinary Journal of Information, Knowledge, and Management* 6.6 (2011): 245–269.
7. Braganza, A., Brooks, L., Nepelski, D., Ali, M., & Moro, R. "Resource management in big data initiatives: Processes and dynamic capabilities." *Journal of Business Research* 70 (2017): 328–337.
8. Büschgens, T., Bausch, A., & Balkin, D. B. "Organizational culture and innovation: A meta-analytic review." *Journal of Product Innovation Management* 30.4 (2013): 763–781.
9. Cichy, C., & Rass, S. "An overview of data quality frameworks." *IEEE Access* 7 (2019): 24634–24648.
10. Crona, B. I., & Parker, J. N. "Learning in support of governance: theories, methods, and a framework to assess how bridging organizations contribute to adaptive resource governance." *Ecology and Society* 17.1 (2012).
11. Fagbore, O. O., Ogeawuchi, J. C., Ilori, O., Isibor, N. J., Odetunde, A., & Adekunle, B. I. "Developing a conceptual framework for financial data validation in private equity fund operations." (2020).
12. Faruq, M. O., & Mollah, M. H. O. R. "Post-GDPR digital compliance in multinational organizations: Bridging legal obligations with cybersecurity governance." *American Journal of Scholarly Research and Innovation* 1.01 (2021): 27–60.
13. Gnan, L., Hinna, A., Monteduro, F., & Scarozza, D. "Corporate governance and management practices: Stakeholder involvement, quality and sustainability tools adoption." *Journal of Management & Governance* 17.4 (2013): 907–937.
14. Goyal, A. "Enhancing engineering project efficiency through cross-functional collaboration and IoT integration." *International Journal of Research and Analytical Reviews* 8.4 (2021): 396–402.
15. Ibrahim, A., Ibrahim, M., & Satar, N. S. M. "Factors influencing master data quality: A systematic review." *International Journal of Advanced Computer Science and Applications* 12.2 (2021).
16. Koch, T., & Windsperger, J. "Seeing through the network: Competitive advantage in the digital economy." *Journal of Organization Design* 6.1 (2017): 6.
17. Korhonen, J. J., Melleri, I., Hiekkanen, K., & Helenius, M. "Designing data governance structure: an organizational perspective." *GSTF Journal on Computing* 2.4 (2013): 11–17.
18. Lis, D., & Otto, B. "Data governance in data ecosystems – insights from organizations." (2020).

19. Maddukuri, N. "Trust in the cloud: Ensuring data integrity and auditability in BPM systems." *International Journal of Information Technology and Management Information Systems* 12.1 (2021): 144–160.
20. Nfuka, E. N., & Rusu, L. "The effect of critical success factors on IT governance performance." *Industrial Management & Data Systems* 111.9 (2011): 1418–1448.
21. Nwaimo, C. S., Oluoha, O. M., & Oyedokun, O. Y. E. W. A. L. E. "Big data analytics: technologies, applications, and future prospects." *Iconic Research and Engineering Journals* 2.11 (2019): 411–419.
22. Selvarajan, G. "Leveraging AI-enhanced analytics for industry-specific optimization: A strategic approach to transforming data-driven decision-making." *International Journal of Enhanced Research in Science, Technology & Engineering* 10 (2021): 78–84.
23. Tett, R. P., Hundley, N. A., & Christiansen, N. D. "Meta-analysis and the myth of generalizability." *Industrial and Organizational Psychology* 10.3 (2017): 421–456.
24. Thatcher, A. "Longevity in a sustainable human factors and ergonomics system-of-systems." *22ª Semana de la Salud Ocupacional* (2016).
25. Vandenbroucke, D., Olijslagers, M., Boguslawski, R., Borzachiello, M. T., Perego, A., & Smith, R. S. "Architectures and standards for spatial data infrastructures and digital government." *KJ-NA-30336-EN-N* (2020).
26. Zhang, R., Indulska, M., & Sadiq, S. "Discovering data quality problems: the case of repurposed data." *Business & Information Systems Engineering* 61.5 (2019): 575–593.

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Joshi, D. "Evaluating Data Quality Improvement Strategies Under Enterprise Data Governance Systems." *Sarcouncil Journal of Public Administration and Management* 1.5 (2022): pp 1-8.