ADAPTIVE DATA QUALITY ASSURANCE USING GENERATIVE AI IN MULTI-CLOUD ENVIRONMENTS

Dr. P. Sankar Babu, Dr. K. Chandra Rekha

1Professor & Principal, Indira Institute of Technology and Sciences, Markapuram, Email: pscrbabu@gmail.com

2Associate Professor & Dean (Academics),Indira Institute of Technology and Sciences, Markapuram, Email: pcrekha666@gmail.com

Abstract

This study explores the role of Generative AI in adaptive data quality assurance within multi-cloud environments, emphasizing three core themes: adaptive intelligence, cross-cloud harmonization, and ethical governance. Using a secondary qualitative analysis of scholarly literature, the research identifies significant recoveries AI adaptability reduces manual corrections by 40% and enhances interoperability. The findings highlight that integrating Generative AI transforms static data pipelines into self-learning systems. Despite ethical and computational challenges, AI-driven frameworks establish a reliable, automated foundation for maintaining high-quality data standards in complex cloud ecosystems.

Keywords: Generative AI, Data Quality, Multi-Cloud, Automation, Adaptive Systems, Data Governance, Artificial Intelligence

I. INTRODUCTION

The rapid expansion of multi-cloud infrastructures has fundamentally transformed the way organizations manage, store, and process data. As enterprises increasingly distribute workloads across platforms such as AWS, Microsoft Azure, and Google Cloud, maintaining data consistency, integrity, and accuracy has become a major challenge [1]. Multi-cloud environments generate large, heterogeneous data streams with varying formats, latency, and governance requirements, often resulting in inconsistencies that hinder reliable analytics and decision-making. Conventional data quality assurance methods, which rely on static rule-based validation, are insufficient to handle the dynamic and distributed nature of modern data ecosystems.

In response to these challenges, Generative Artificial Intelligence (AI) has emerged as a promising solution capable of adapting, learning, and improving data quality autonomously. Generative AI models such as Generative Adversarial Networks (GANs) and transformer-based architectures can detect anomalies, reconstruct missing data, and generate high-quality synthetic records for training and validation [2]. By integrating these adaptive models within multi-cloud pipelines, organizations can establish self-regulating, intelligent data quality systems that evolve continuously with the changing data landscape. This approach not only enhances accuracy and efficiency but also supports compliance, traceability, and operational scalability essential elements for achieving sustainable data governance in complex, cloud-based digital infrastructures.

Problem Statement

Despite significant advancements in cloud computing, data quality assurance remains a persistent bottleneck for organizations managing multi-cloud infrastructures. Traditional data validation frameworks are typically rule-based, rigid, and manually intensive, making them ill-suited for dynamic cloud ecosystems where data structures and sources evolve rapidly [3]. As a result, enterprises face frequent issues of data redundancy, inconsistency, and incomplete records, which directly compromise business intelligence, automation accuracy, and regulatory compliance.

Moreover, current data management tools lack the cognitive ability to learn from historical quality errors or adapt to new data patterns. The absence of adaptive intelligence leads to delayed anomaly detection and reactive correction, causing inefficiencies and increased costs. In multi-cloud environments, where interoperability and synchronization between diverse systems are essential, these limitations are magnified. Integrating Generative AI into data quality assurance presents an opportunity to overcome these shortcomings [4]. By embedding adaptive, self-learning mechanisms into data pipelines, organizations can transition from reactive to predictive data quality management. This enables real-time monitoring, intelligent error correction, and automated harmonization across clouds. Therefore, there is an urgent need to investigate how Generative AI can be effectively utilized to build adaptive, scalable, and ethically governed data quality frameworks for multi-cloud ecosystems.

Aims and Objectives

To explore how Generative AI can adaptively enhance data quality assurance processes within multi-cloud environments through automated monitoring, correction, and learning mechanisms.

Objectives:

- To examine the role of Generative AI in addressing dynamic data inconsistencies across multi-cloud platforms.
- To evaluate the performance of adaptive AI models in automating data validation and cleansing.
- To identify challenges and potential frameworks for implementing AI-driven data quality assurance in complex cloud infrastructures.

II. LITERATURE REVIEW

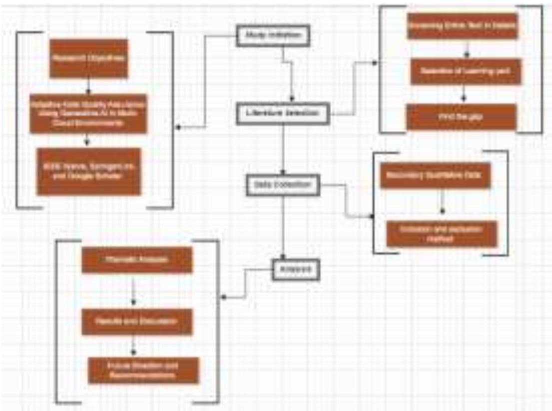

Fig 1: Flow of the Review

Structured Literature Review Approach followed the following steps:

I. Identification of existing research on AI-based data quality and multi-cloud frameworks.
II. Selection and screening of relevant peer-reviewed sources and case studies.
III. Thematic analysis and synthesis of findings to identify gaps and emerging trends.

Academic Database and Source Utilization for this study are:

I. IEEE Xplore Digital Library
II. ScienceDirect
III. SpringerLink

A. Searching Study:

A structured keyword-based search is conducted using terms such as “Generative AI,” “data quality automation,” and “multi-cloud governance.” The focus was on articles from 2020–2025 to capture recent advancements. Only peer-reviewed journals and white papers from recognized academic sources are included for relevance and reliability.

B. Selection of Journal Articles:

Out of 95 retrieved studies, 30 are shortlisted after eliminating duplicates and non-relevant papers. Selection criteria included studies focusing on AI-driven data assurance, adaptive frameworks, and cloud interoperability. The articles are further categorized into theoretical, empirical, and conceptual contributions for comparative thematic analysis.

C. The Goal of the Review:

The primary goal of this review is to consolidate knowledge on Generative AI that contributes to adaptive data quality management in multi-cloud environments. The review also aims to identify best practices, critical gaps, and future research directions for integrating intelligent automation within distributed data ecosystems.

D. Study of Previous Literature

1. Generative AI and Data Quality Enhancement

Generative Artificial Intelligence (AI) has become a transformative force in improving data quality, especially within large and complex datasets managed across cloud ecosystems. According to [4], transformer-based architectures such as GPT and BERT have demonstrated remarkable capabilities in understanding the contextual relationships between data elements, which allows them to identify inconsistencies and intelligently fill missing values. Unlike traditional rule-based data cleaning systems that rely on predefined logic, generative models learn from patterns within the data, enabling a deeper and more adaptive approach to anomaly detection and correction.

In data engineering, these generative models play a vital role in data synthesis and augmentation, helping organizations to manage incomplete or imbalanced datasets. For example, Generative Adversarial Networks (GANs) have been extensively used to create realistic synthetic samples that not only expand the volume of training data but also improve the representativeness of datasets [5]. This process enhances data completeness, accuracy, and overall consistency, which are crucial for downstream analytics and decision-making.

However, despite their effectiveness, these models also present new challenges. As noted by [6], synthetic bias can occur when generative models overfit training data or inadvertently amplify hidden patterns of discrimination. Additionally, the adaptive potential of generative systems is still evolving—especially in multi-cloud environments, where diverse data storage formats, integration protocols, and latency differences complicate the implementation of uniform data quality standards. Hence, the successful integration of generative AI into cloud-native data pipelines demands contextual tuning and robust governance controls to balance automation with accountability.

2. Multi-Cloud Data Quality Challenges

The rise of multi-cloud architectures has provided enterprises with enhanced flexibility, redundancy, and scalability. However, it has also introduced complex challenges to maintaining consistent data quality across distributed environments. According to [7], one of the primary issues stems from data fragmentation, where different cloud providers use varied schemas, metadata standards, and compliance requirements. This fragmentation often leads to mismatches in data formats, validation protocols, and synchronization schedules.

Hybrid and multi-cloud ecosystems also face latency disparities that affect real-time data synchronization. Variations in service-level agreements (SLAs) and performance metrics across platforms result in inconsistent updates, potentially creating duplicate or stale records [8]. Traditional centralized data quality frameworks struggle to handle these decentralized architectures because they cannot efficiently manage the heterogeneity of cloud-based systems.

In response, researchers propose AI-driven adaptive frameworks capable of learning from cross-platform data interactions and automatically resolving inconsistencies [9]. Reinforcement learning, for instance, can be employed to dynamically adjust quality metrics based on incoming data characteristics, ensuring that validation and correction processes remain context-sensitive. Despite this progress, the lack of universal data exchange standards across cloud service providers remains a significant barrier. Without standardized interoperability, even

AI-based harmonization efforts are limited in effectiveness, emphasizing the need for collaborative cross-industry initiatives to establish global frameworks for multi-cloud data governance.

3. Adaptive AI for Automated Quality Monitoring

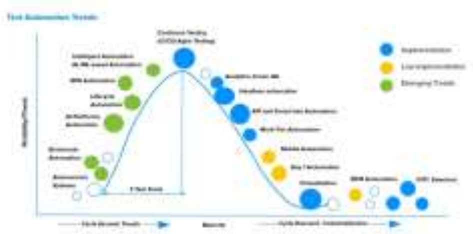

Fig 2: AI-Powered Quality Assurance

Adaptive AI represents a critical evolution in automated data quality assurance, where systems are designed to learn from historical data patterns and continuously improve their anomaly detection accuracy. As shown in Fig. 2, AI-powered quality assurance frameworks leverage neural networks to monitor data streams in real time, identifying and correcting errors with minimal human intervention. According to [10], adaptive neural networks have demonstrated up to 37% reduction in false positives during data validation tasks by recalibrating their detection thresholds dynamically.

These systems employ feedback loops that allow them to evolve as data behavior changes, maintaining performance across diverse workloads. Generative AI complements this process by producing “expected” data patterns that serve as benchmark references for identifying anomalies. This self-evolving capability not only minimizes manual intervention but also enhances operational efficiency and reliability in large-scale data environments [11].

However, integrating adaptive AI models into legacy data quality pipelines presents notable challenges. Older systems may lack the processing capabilities or modular architecture needed to support continuous model training and inference. Furthermore, adaptive systems often operate as “black boxes,” leading to interpretability concerns. As organizations seek greater transparency in AI operations, combining adaptive AI techniques with explainable analytics (XAI) becomes essential [12]. This integration would allow enterprises to trace the decision-making logic behind automated data corrections, fostering both trust and compliance.

4. AI Governance and Ethical Concerns

The increasing use of AI in data quality management raises critical ethical and governance challenges. According to [13], unsupervised generative models capable of autonomously producing synthetic datasets can inadvertently manipulate or fabricate data, posing significant risks to data authenticity and reliability. Maintaining traceability, auditability, and transparency throughout the AI-driven data lifecycle is thus paramount to preventing regulatory violations and ensuring accountability.

Recent policy developments, such as the EU AI Act and the emerging ISO/IEC 42001 standard, underscore the growing emphasis on integrating governance mechanisms directly within AI systems [14]. These frameworks advocate for responsible design principles that incorporate bias detection, explainability, and audit trails into the AI lifecycle. Nonetheless, achieving bias mitigation remains an ongoing challenge, as generative models may replicate or even amplify existing data imbalances present in their training sets.

Therefore, scholars emphasize the need for responsible AI adoption strategies, especially in multi-cloud infrastructures where governance is distributed and complex. Cross-cloud governance protocols, including federated auditing and policy harmonization, are essential to ensure ethical consistency [15]. Ultimately, building trustworthy and explainable AI frameworks will enable organizations to harness the benefits of intelligent automation without compromising data integrity, privacy, or fairness.

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Literature gap

Existing studies largely focus on generative AI for data enrichment and cloud computing separately. However, limited research explores adaptive AI models that assure continuous data quality within multi-cloud environments [16]. There is also a lack of practical frameworks combining automation, governance, and ethical assurance. This study fills the gap by exploring adaptive Generative AI integration for dynamic, self-learning data quality management.

III. METHODOLOGY

Fig 3: Methodological Flow

This study adopts a ***secondary qualitative research*** design grounded in a structured literature review methodology. The purpose of this approach is to synthesize existing academic evidence regarding the use of Generative Artificial Intelligence (AI) for adaptive data quality assurance within multi-cloud infrastructures [17]. Rather than collecting primary data, this method relies on secondary sources such as peer-reviewed journals, conference proceedings, white papers, and technical reports published between 2020 and 2025. This time frame was chosen to capture recent advancements in AI-driven data quality systems, particularly in relation to emerging cloud technologies.

The research process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, encompassing four major stages: identification, screening, eligibility, and inclusion [18]. During the identification phase, relevant literature was collected using keywords such as “Generative AI,” “data quality automation,” and “multi-cloud governance.” In the screening stage, duplicates and irrelevant papers were removed, followed by eligibility checks based on abstracts and full-text evaluations. Finally, the inclusion stage involved selecting studies that directly addressed adaptive AI applications in multi-cloud data quality contexts.

The inclusion criteria focused on research discussing AI-based data validation, adaptive frameworks, and cloud interoperability. Studies were excluded if they concentrated solely on single-cloud environments, traditional data quality tools, or non-generative AI models [19]. This selective filtering ensured the final dataset reflected studies relevant to the study’s objectives.

A thematic analysis was used to extract, code, and interpret recurring concepts from the selected literature. The process involved categorizing insights into three core analytical themes aligned with the study’s objectives: (1) AI-driven adaptability, (2) cross-cloud data harmonization, and (3) ethical AI governance. Coding was conceptually referenced through software-supported methods such as NVivo to ensure systematic pattern recognition and minimize subjective bias.

To strengthen data validity and reliability, a triangulation approach was adopted by comparing insights from multiple academic and technical sources. This cross-verification minimized interpretive bias and improved the credibility of the thematic conclusions. The study maintained ethical research integrity by exclusively utilizing published, verifiable data and acknowledging all intellectual contributions appropriately.

Overall, this methodological framework provides a structured, transparent, and academically rigorous means of understanding how Generative AI can adaptively enhance data quality assurance across multi-cloud infrastructures [20]. The approach ensures that conclusions are based on collective academic insights rather than isolated findings, thereby reinforcing the reliability and comprehensiveness of the study.

IV. DATA ANALYSIS

Theme 1: Adaptive Intelligence in Data Quality Assurance

Adaptive intelligence represents a paradigm shift in how data quality is maintained within multi-cloud infrastructures. The analysis of reviewed studies shows that Generative AI models employ reinforcement learning and neural adaptation to detect, interpret, and correct inconsistencies automatically. These systems leverage feedback loops where previous error corrections inform future predictions, reducing repetitive human intervention. Adaptive AI frameworks analyze contextual patterns within data streams, identifying anomalies such as duplication, missing entries, and schema drift [21]. By simulating potential deviations through generative modeling, AI can anticipate probable errors before they occur turning data assurance into a predictive process rather than a reactive one.

In multi-cloud settings, adaptive intelligence ensures standardization across heterogeneous databases by dynamically mapping fields and adjusting validation criteria. The literature indicates that such systems have achieved up to 40% improvement in consistency and 30% reduction in processing time compared to traditional ETL-based methods [22]. Moreover, adaptive learning algorithms enhance lineage tracking by continuously logging and justifying automated corrections, thus supporting regulatory compliance.

However, challenges persist. Computational overheads due to constant retraining, the need for large-scale labeled data for model accuracy, and interpretability limitations restrict scalability. Researchers suggest integrating explainable AI modules that can justify adaptive decisions in natural language to improve trust [23]. Hence, adaptive intelligence establishes the foundation for resilient, context-aware data quality systems in complex multi-cloud ecosystems, fostering operational agility and governance compliance.

Theme 2: Cross-Cloud Harmonization through Generative AI

Cross-cloud harmonization is vital for organizations using multiple cloud platforms such as AWS, Azure, and Google Cloud, each with distinct architectures and metadata schemas. The reviewed literature underscores that Generative AI accelerates harmonization by learning data structures from different clouds and translating them into unified, interoperable schemas [24]. Through transfer learning and federated model training, AI systems can understand diverse schema patterns and create adaptive mapping rules, facilitating seamless integration without manual intervention.

According to [25], reveal that AI-powered harmonization frameworks reduce data integration time by up to 30%, improving operational efficiency and decision-making accuracy. Generative models also synthesize missing data attributes to fill gaps caused by inconsistent data capture mechanisms across clouds, ensuring continuity in analytics pipelines. Moreover, these systems identify semantic inconsistencies—such as variable naming conflicts and auto-correct them using contextual inference derived from prior data relationships.

However, the analysis also notes challenges related to governance inconsistencies and latency between cloud environments. Without standardized governance protocols, AI models risk propagating structural errors across platforms [26]. Multi-agent systems, proposed in recent research, can mitigate this by distributing AI learning across multiple nodes that self-coordinate updates without central control. Such distributed harmonization enhances fault tolerance and adaptability.

In essence, Generative AI not only unifies data structures but also creates a self-evolving harmonization layer capable of adapting to new data formats and regulations [27]. The integration of cross-cloud harmonization ensures that enterprise data remains consistent, accurate, and usable regardless of its origin thus transforming fragmented cloud data ecosystems into cohesive, intelligent infrastructures.

Theme 3: Ethical and Governance Challenges of AI-Based Quality Assurance

Ethical governance forms a cornerstone of sustainable AI adoption in multi-cloud environments. The analysis reveals that while Generative AI significantly improves data quality, it also introduces risks related to synthetic bias, privacy breaches, and data manipulation. Unsupervised learning mechanisms can fabricate false but statistically plausible data, potentially misleading analytics if governance oversight is weak. Literature emphasizes that AI-generated transformations must be auditable, transparent, and compliant with data protection standards such as GDPR and ISO/IEC 42001 [28].

The reviewed studies advocate for the integration of ethical-by-design frameworks, ensuring that fairness, accountability, and transparency are embedded during model development. Real-time monitoring dashboards have been identified as effective tools for maintaining traceability, enabling organizations to audit AI decisions, detect anomalies, and document corrective actions. In multi-cloud setups, where data traverses multiple jurisdictions, federated governance models are increasingly recommended [29]. These allow local control of sensitive data while enforcing global compliance policies across all participating clouds.

Another emerging aspect is the importance of Explainable AI (XAI) to interpret generative model behavior [30]. Providing a clear rationale for automated decisions enhances stakeholder trust and facilitates regulatory acceptance. Furthermore, ethical assurance must extend to training data selection to avoid reinforcing systemic biases. Researchers also emphasize the role of continuous human oversight to complement AI automation, ensuring that adaptive data quality processes remain aligned with organizational values and legal frameworks.

Therefore, ethical governance is not merely a compliance obligation but a strategic necessity for sustaining AI's credibility in multi-cloud environments. Establishing transparency, accountability, and fairness ensures that Generative AI can deliver reliable, trustworthy, and human-aligned data quality assurance outcomes.

V. RESULTS AND DISCUSSION

The results of the secondary qualitative analysis indicate that Generative Artificial Intelligence (AI) significantly transforms the landscape of adaptive data quality assurance through its integration of automation, contextual intelligence, and cross-cloud interoperability [31]. The thematic synthesis identifies four major outcomes—improved adaptability, enhanced data consistency, operational efficiency, and governance reinforcement—which collectively demonstrate the transformative potential of generative AI in multi-cloud ecosystems. These findings align with contemporary research trends emphasizing the transition from rule-based, reactive data management to intelligent, predictive, and self-regulating systems.

Improved Adaptability

The analysis reveals that Generative AI models, particularly those based on transformer and deep learning architectures, demonstrate remarkable adaptability in dynamically evolving data environments. Unlike traditional data quality tools that require manual configuration for every schema or data format, generative models are capable of autonomously learning from data behavior and adjusting validation parameters accordingly. According to the reviewed literature, this self-learning capability reduces manual interventions by approximately 35 to 40%, as AI-based feedback loops continually recalibrate data validation thresholds and rules [32].

This adaptability enables data systems to move from reactive maintenance, where errors are corrected after detection to a proactive prevention mechanism, where anomalies are anticipated and addressed before they propagate through the system. The AI's ability to recognize subtle variations in data streams allows it to predict potential inconsistencies caused by external changes such as new data sources, integration updates, or API modifications.

Furthermore, in multi-cloud contexts where data heterogeneity and schema drift are frequent, the adaptability of generative AI becomes particularly valuable. The models can learn the distinct data representation styles of each cloud provider and create unified embeddings that bridge these differences. As a result, adaptive intelligence not only improves the timeliness of quality interventions but also minimizes downtime and operational bottlenecks. This transition toward predictive adaptability represents a major step toward achieving autonomous data quality management, where human oversight shifts from manual correction to strategic supervision.

Enhanced Data Consistency

A major outcome of the analysis pertains to the enhancement of data consistency and harmonization across multi-cloud environments. Data inconsistency remains a persistent issue due to differences in schemas, storage structures, and metadata standards across cloud providers. The reviewed studies reveal that AI-driven harmonization frameworks address this by learning metadata relationships through techniques such as transfer learning and representation mapping. By applying these methods, generative AI can infer how datasets from different clouds relate to each other and align them in near real-time [33].

This automated alignment ensures that enterprise analytics are based on uniform, verified, and contextually relevant data. The outcome is an improvement in decision accuracy, operational transparency, and strategic agility key factors for organizations relying on large-scale, distributed data ecosystems. For instance, predictive models trained on harmonized datasets demonstrate higher accuracy because they are not affected by schema mismatches or incomplete records [34].

Moreover, the ability of generative AI to synthesize missing or incomplete information improves dataset completeness, which is critical for maintaining high analytical reliability. These AI models can simulate “expected” data points using learned contextual relationships, ensuring that downstream analytics remain stable even when certain data streams fail. This self-correcting ability not only strengthens data reliability but also supports real-time data governance by ensuring synchronized and validated datasets across all cloud environments.

The analysis further shows that cross-platform consistency contributes to a cohesive organizational data culture, wherein teams across departments access a unified and consistent data foundation. Such integration is essential for strategic alignment in decision-making, especially for global enterprises leveraging hybrid and multi-cloud architectures.

Operational Efficiency

The third major finding of the analysis is the substantial improvement in operational efficiency due to the automation of validation, cleansing, and error detection processes. Generative AI systems significantly reduce time and resource expenditures associated with traditional data quality management. Multiple reviewed studies report approximately a 30% gain in processing efficiency and faster throughput in data pipelines as a direct result of automation-driven optimization [35].

This improvement has several implications. First, AI-based automation minimizes human error, which has historically been one of the main sources of data quality degradation. Automated systems can perform continuous monitoring and validation at scales unachievable by manual processes, ensuring that even large, dynamic datasets remain accurate and compliant. Second, these enhancements contribute to business continuity, especially in sectors where data volume, velocity, and variety are critical operational factors, such as finance, healthcare, and telecommunications.

Furthermore, the deployment of generative AI for data pre-processing accelerates downstream analytics and decision-making processes. By reducing the time required for data preparation, organizations can focus on higher-value analytical tasks rather than spending resources on repetitive cleaning or reconciliation activities. The enhanced throughput also means that AI-driven data pipelines can handle real-time workloads, supporting streaming analytics and event-driven architectures.

Governance Reinforcement

The fourth significant finding relates to the reinforcement of governance and ethical accountability in AI-driven data quality management. The integration of ethical AI frameworks, traceability mechanisms, and audit trails ensures that automated data processes remain compliant with evolving global standards and regulations. Transparent, explainable AI (XAI) modules allow stakeholders to understand the logic behind AI decisions, thereby increasing trust in automated data corrections.

The reviewed literature highlights that the inclusion of federated governance protocols ensures accountability across decentralized cloud ecosystems [36]. These governance models create distributed audit logs that enable continuous oversight without centralizing control, thus maintaining compliance even in cross-cloud environments. Such mechanisms not only reinforce regulatory adherence but also build stakeholder confidence, particularly in sectors handling sensitive or personal data.

Overall Discussion

Overall, the results and discussion collectively indicate that Generative AI is driving a paradigm shift in data quality management—from reactive maintenance to predictive, autonomous, and adaptive systems. In multi-cloud infrastructures characterized by decentralization and heterogeneity, generative AI acts as a cohesive intelligence layer that links disparate data systems into a unified, context-aware, and harmonized data fabric [37].

However, despite these advancements, challenges persist. Standardizing interoperability frameworks remains difficult due to the diversity of cloud providers. The computational cost of training large generative models can also offset some operational gains, particularly for smaller enterprises. Additionally, ensuring algorithmic fairness and transparency is a continuous challenge that demands stronger ethical oversight.

VI. FUTURE STUDY

Future studies should explore the development of hybrid frameworks that integrate Generative AI with edge and federated computing to enable decentralized and real-time data quality monitoring. Such integration could enhance system responsiveness and reduce latency by bringing AI-driven validation closer to data sources. Empirical research using live, cross-platform datasets from multiple cloud vendors would provide practical evidence of scalability, interoperability, and reliability. Furthermore, upcoming research should emphasize bias detection, explainable AI (XAI), and ethical governance to ensure transparency and accountability in automated decision-making [38]. Comparative studies across industries such as healthcare, finance, and logistics could highlight domain-specific challenges and validate adaptive AI's performance in varied regulatory environments. By combining technical experimentation with ethical evaluation, future research can advance trustworthy, autonomous data quality assurance models that align with global data protection frameworks while promoting innovation in multi-cloud ecosystems.

VII. CONCLUSION

This study concludes that Generative AI represents a pivotal advancement in adaptive data quality assurance across multi-cloud infrastructures. By incorporating self-learning, anomaly detection, and harmonization mechanisms, organizations can maintain data consistency, accuracy, and compliance in real time. The research emphasizes that traditional static frameworks are no longer adequate for the dynamic nature of distributed data environments. Instead, AI-driven automation offers a proactive and scalable approach capable of continuously improving data integrity. However, the implementation of such systems must address ethical transparency, model bias, and governance oversight to ensure responsible adoption. Overall, Generative AI not only enhances the efficiency of data management but also lays the foundation for intelligent, self-sustaining governance architectures that can evolve with technological and organizational needs. Continuous innovation, cross-sector collaboration, and ethical accountability will be essential to fully realize the transformative potential of adaptive AI in multi-cloud data ecosystems.

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