World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

Responsible AI in database systems: Governance frameworks for generative AI data access

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World Journal of Advanced Research and Reviews, 2025, 26(02), 3017-3026

Publication history: Received on 09 April 2025; revised on 18 May 2025; accepted on 20 May 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.26.2.1942

Abstract

This article introduces a novel governance framework addressing the unique challenges of managing generative AI data within database systems. While extensive literature examines responsible AI principles in theory, a significant gap exists in translating these ethical frameworks into practical implementation at the database layer. The article presents a comprehensive approach that bridges this divide through a layered architecture incorporating fine-grained access controls, comprehensive lineage tracking, and automated policy enforcement mechanisms specifically designed for generative AI workloads. The article addresses distinctive challenges, including complex data transformations, synthetic content generation, purpose limitation in repurposed data, and evolving consent requirements that traditional governance models fail to adequately manage. The article demonstrates substantial improvements in governance effectiveness compared to conventional approaches. This article provides database administrators and AI practitioners with concrete strategies for maintaining ethical boundaries throughout the data lifecycle while enabling responsible innovation. The framework establishes a foundation for operationalizing AI ethics at the infrastructure level, ensuring that governance considerations become integral to system design rather than retrospective considerations

Keywords: Generative AI Governance; Database Ethics Framework; Data Lineage Tracking; Automated Policy Enforcement; Responsible AI Implementation

1. Introduction

The rapid advancement of generative artificial intelligence technologies has transformed data processing paradigms across industries, creating powerful capabilities for synthesizing new content, augmenting decision-making processes, and automating complex analytical tasks [1]. While these innovations offer unprecedented opportunities, they simultaneously introduce novel governance challenges at the fundamental database layer that supports AI systems. Despite extensive literature examining ethical AI frameworks, responsible innovation principles, and algorithmic accountability, there exists a significant research gap regarding the practical implementation of these principles within database management systems specifically designed for generative AI applications.

Traditional data governance models were primarily developed for structured, relational databases with relatively predictable access patterns and clear data ownership boundaries. However, generative AI applications fundamentally disrupt these assumptions by continually synthesizing, transforming, and repurposing data in ways not anticipated by conventional governance policies. These models ingest vast quantities of training data, create derivative works, and may utilize information for purposes far removed from its original context—all while operating at a scale and complexity that challenges manual oversight.

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This article addresses this critical gap by proposing a layered governance framework specifically designed for database systems supporting generative AI workloads. The article integrates fine-grained access controls, comprehensive lineage tracking mechanisms, and automated policy enforcement protocols that maintain ethical AI principles throughout the data lifecycle. Unlike theoretical frameworks that often remain disconnected from technical implementation, this work bridges theory and practice by providing database administrators and AI practitioners with concrete strategies for responsible AI data management.

The significance of this article lies in its practical orientation toward operationalizing responsible AI principles at the database layer—the fundamental infrastructure upon which generative AI applications depend. By addressing governance challenges at this foundational level, organizations can build ethical considerations directly into the technical architecture supporting AI systems rather than attempting to retrofit governance onto existing implementations. This article contributes both a theoretical framework and implementation guidance for establishing responsible data practices that align with broader ethical AI objectives while addressing the unique challenges posed by generative technologies.

2. Literature Review

2.1. Current responsible AI frameworks and principles

Responsible AI frameworks have evolved significantly in recent years, with major initiatives from both industry and academia establishing foundational principles. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems highlights transparency, accountability, and non-maleficence as key pillars [2]. Similarly, organizations have developed practical implementations of these principles, though most focus primarily on model development rather than underlying data infrastructure. These frameworks generally emphasize fairness, explainability, privacy, and security, but often lack specific guidance for database-level controls.

2.2. Traditional database governance approaches

Conventional database governance has historically centered on structured data management through role-based access control (RBAC), data classification schemas, and audit logging. Enterprise data governance frameworks typically implement hierarchical permission structures with designated data stewards and owners. The focus has primarily been on maintaining data quality, ensuring regulatory compliance, and managing access rights within well-defined organizational boundaries—a paradigm ill-suited for the fluid nature of generative AI workloads.

2.3. Limitations of existing models for generative AI applications

Existing governance models face significant limitations when applied to generative AI contexts. Traditional approaches assume relatively static data usage patterns, whereas generative AI systems dynamically combine and transform data. Current frameworks lack mechanisms for tracking derivative works, managing synthetic data provenance, and enforcing ethical boundaries on AI-generated outputs. Additionally, the scale of data processing in modern AI systems overwhelms manual governance processes designed for human-paced interactions.

2.4. Related work on data lineage and provenance

Recent research on data lineage has produced promising approaches for tracking data transformations. Work by Herschel et al. explores fine-grained provenance tracking in heterogeneous data environments, though primarily focused on analytical rather than generative workloads. Similarly, emerging research on computational provenance offers potential mechanisms for tracking AI-mediated data transformations, but these approaches require adaptation for the unique characteristics of generative models.

2.5. Regulatory landscape affecting AI data governance

The regulatory environment surrounding AI data governance continues to evolve rapidly. The European Union's General Data Protection Regulation (GDPR) established important precedents regarding data subject rights and algorithmic transparency, while more recent proposals like the EU AI Act specifically address high-risk AI applications. In the United States, sectoral privacy regulations and emerging state laws create a complex compliance landscape that database systems must navigate, further complicating governance requirements.

3. Methodology

3.1. Research design and approach

This research employs a mixed-methods approach combining theoretical framework development with practical implementation testing. We utilize a design science methodology to develop governance artifacts specifically tailored to generative AI database requirements. The research proceeds through three phases: (1) problem identification through literature review and expert interviews, (2) artifact design and development, and (3) evaluation through case studies and expert validation.

3.2. Data collection methods

Data collection involved systematic literature reviews across three domains: responsible AI frameworks, database governance practices, and generative AI applications. We supplemented this theoretical foundation with semi-structured interviews of 18 database administrators and AI practitioners from organizations actively implementing generative AI systems. Additionally, we analyzed 12 case studies of governance failures to identify common patterns and challenges.

3.3. Analysis framework

Our analysis employs a multi-dimensional framework examining governance mechanisms across four key domains: access control granularity, lineage tracking capabilities, policy enforcement automation, and ethical principle alignment. Each domain is evaluated against effectiveness criteria derived from both practical implementation requirements and established ethical AI principles. This structured approach enables systematic assessment of governance mechanisms against both technical and ethical standards.

3.4. Limitations and boundaries of study

This research focuses specifically on relational and document-oriented database systems supporting generative AI applications, and may not generalize to all data storage paradigms. Additionally, our evaluation primarily addresses enterprise contexts rather than consumer applications, potentially limiting applicability to personal or small-scale AI deployments. The rapidly evolving nature of generative AI technologies also means that governance requirements will continue to evolve beyond our current analysis.

4. Generative AI Data Governance Challenges

4.1. Unique characteristics of generative AI data usage patterns

Generative AI systems exhibit distinctive data usage patterns that challenge traditional governance approaches. These systems typically consume vast quantities of training data across multiple modalities, operate through complex transformation processes that obscure original data relationships, and continuously evolve through incremental learning. Unlike transactional systems with predictable data flows, generative AI applications dynamically combine information sources in ways that traditional access controls cannot effectively manage. The probabilistic nature of generative outputs further complicates governance, as the relationship between inputs and outputs becomes increasingly non-deterministic [3].

4.2. Synthesis and transformation issues

The synthetic data capabilities of generative AI create significant governance challenges. These systems can combine elements from multiple sources to create novel outputs that appear authentic but exist nowhere in the original dataset. This capability raises questions about intellectual property attribution, factual accuracy, and appropriate use constraints. When generative models transform data into new representations, traditional policies focused on raw data access become insufficient, as they fail to address derivative works that may retain sensitive characteristics while appearing superficially distinct from source materials.

4.3. Data repurposing scenarios and implications

Generative AI systems frequently repurpose data for uses far removed from the original collection context. Training data gathered for one purpose becomes embedded in models deployed for entirely different applications, creating significant governance gaps. For example, text corpora collected for linguistic research may influence generative models later used in healthcare decision support, raising questions about domain appropriateness and ethical boundaries.

Traditional purpose limitation principles become difficult to enforce when data influences model behaviors in subtle, distributed ways that resist clear categorization.

4.4. Consent and privacy considerations

Consent mechanisms designed for direct data usage break down in generative AI contexts where individual data points influence model behaviors in complex, unpredictable ways. Traditional notice and consent frameworks struggle to meaningfully inform data subjects about potential generative applications of their information. Privacy protections based on direct identifiability also prove inadequate when generative models can synthesize realistic yet technically "anonymous" profiles that nonetheless reveal sensitive characteristics of training populations.

4.5. Case studies illustrating governance failures

Recent governance failures highlight the inadequacy of current approaches. In one healthcare organization, a generative AI system trained on patient records subsequently produced realistic but fictitious medical histories that clinicians mistakenly incorporated into treatment decisions. Another case involved a financial institution whose database governance failed to prevent sensitive customer transaction data from influencing a customer service AI that inadvertently revealed spending patterns to unauthorized users. These failures demonstrate how traditional isolation-based governance models collapse when generative capabilities bridge previously separate data domains.

5. Proposed Layered Governance Framework

5.1. Architectural overview

Our proposed governance framework implements a layered architecture designed specifically for database systems supporting generative AI workloads. This approach moves beyond traditional perimeter-based security models toward a contextual governance system that maintains awareness of data flows throughout the AI lifecycle. The framework comprises three interconnected components: fine-grained access controls, lineage tracking systems, and automated policy enforcement. These components operate across five architectural layers: physical storage, logical data organization, transformation processes, model integration, and output management.

5.2. Component 1: Fine-grained access control mechanisms

The access control component introduces attribute-based permissions that extend beyond traditional role-based models to incorporate context-sensitive factors including purpose limitations, data sensitivity classifications, and model application constraints. This component implements a policy language specifically designed for generative AI workloads that enables administrators to specify acceptable transformation boundaries and permissible synthesis operations. Unlike traditional database permissions focused on table-level access, these controls maintain policy adherence through complex transformation chains by attaching persistent governance metadata to data elements [4].

5.3. Component 2: Comprehensive lineage tracking systems

The lineage tracking component maintains continuous provenance information throughout data transformation processes. This system records transformation operations, maintains derivation histories for synthetic outputs, and preserves attribution chains even through complex model interactions. Implementation leverages both blockchain-inspired immutable logs and semantic relationship graphs to maintain verifiable records of data providence. This approach enables governance systems to answer critical questions about how specific information influences generative outputs while supporting auditability and accountability requirements.

5.4. Component 3: Automated policy enforcement protocols

Automated enforcement protocols operationalize governance rules through active monitoring and intervention mechanisms. This component employs policy-aware middleware that intercepts database operations, evaluates compliance with established governance rules, and enforces appropriate constraints. The enforcement system implements both preventative controls that block policy violations and detective mechanisms that flag potential governance issues for human review. Machine learning techniques identify potential policy violations through anomaly detection, while explainable AI components provide administrators with clear rationales for enforcement decisions.

5.5. Integration points with existing database infrastructure

The framework integrates with existing database infrastructure through standardized interfaces including extended SQL commands for governance policy specification, API extensions for governance metadata exchange, and monitoring

hooks for major database platforms. Implementation leverages existing extensibility mechanisms in common database systems rather than requiring wholesale replacement. The architecture supports gradual adoption through modular components that can be implemented independently, while providing comprehensive governance when deployed as an integrated solution.

Table 1 Comparison of Traditional vs. Proposed Governance Framework for Generative AI [3-7]

Governance Aspect	Traditional Database Governance	Proposed Layered Governance Framework
Access Control Mechanisms	Role-based access control (RBAC) with static permissions	Attribute-based controls with context-sensitive factors including purpose limitations and model application constraints
Lineage Tracking	Basic audit logs of direct access events	Comprehensive provenance tracking through complex transformations using blockchain-inspired logs and semantic relationship graphs
Policy Enforcement	Manual review and static rule checking	Automated enforcement with preventative controls and machine learning-based anomaly detection
Governance Coverage	36% coverage of generative AI requirements	94.1% coverage across data flows with appropriate controls
Synthetic Data Handling	Essentially no governance capabilities	93% policy compliance through tested synthetic generation scenarios
Performance Impact	Minimal overhead (<5%)	Optimized implementation with 8-12% overhead

6. Implementation Guidelines

6.1. Technical requirements and specifications

Implementing the proposed governance framework requires specific technical infrastructure to support its layered components. Organizations must establish a metadata repository that maintains governance information separate from primary data storage, enabling policy persistence across system changes. Hardware specifications should accommodate additional processing overhead for real-time policy evaluation, with recommended minimum increases of 15-20% in database server capacity. Supporting infrastructure must include secure API gateways for cross-system policy coordination and dedicated policy storage with high-availability requirements comparable to production database systems [5].

6.2. Database system adaptations

Adapting existing database systems requires extensions to core functionality through both native features and middleware components. Relational databases require enhanced trigger mechanisms that invoke governance checks before data transformation operations, while document stores need schema validation extensions that incorporate ethical constraints. Both system types benefit from extended query planners that incorporate governance considerations into execution paths. Implementation approaches include developing custom extensions for major platforms (PostgreSQL, MongoDB), deploying governance-aware proxy layers, and utilizing existing policy enforcement points within enterprise database systems.

6.3. Policy template development

Organizations should develop governance policy templates addressing common generative AI scenarios, establishing standardized approaches to recurring governance challenges. Templates should cover training data ingestion controls, transformation boundaries for sensitive data categories, permissible synthesis operations, and output filtering requirements. Each template incorporates machine-readable policy rules and human-readable rationales explaining governance decisions. The implementation establishes a policy hierarchy that resolves conflicts through explicit priority levels and inheritance mechanisms, ensuring consistent governance across complex data environments.

6.4. Monitoring and auditing mechanisms

Comprehensive monitoring capabilities must track governance decisions throughout the data lifecycle. Implementation requires instrumentation at key transaction points, capturing both allowed and denied operations with sufficient context for meaningful analysis. Audit mechanisms should employ tamper-resistant logging techniques that prevent retroactive policy manipulation, while providing sufficient granularity for meaningful compliance verification. These mechanisms should support both technical audits of system behavior and business-oriented reviews of governance effectiveness, bridging the gap between operational implementation and organizational governance objectives.

6.5. Performance considerations

Performance impact represents a significant implementation concern, requiring careful optimization to maintain acceptable system responsiveness. Benchmarking indicates that naïve implementations can introduce 30-50% performance overhead, but optimized approaches reduce this to 8-12% through techniques like policy caching, parallel evaluation, and tiered enforcement based on data sensitivity. Implementations should employ adaptive enforcement that applies appropriate scrutiny based on operation risk levels, reserving intensive analysis for high-risk transformations while applying lightweight checks to routine operations.

7. Validation and Evaluation

7.1. Framework testing methodology

Validation employed a multi-phase testing methodology to evaluate the framework's effectiveness across diverse scenarios. Initial testing utilized synthetic workloads simulating common generative AI patterns, including training data ingestion, model fine-tuning, and inference operations. These controlled experiments established baseline effectiveness measures. Subsequent testing incorporated production database traces from cooperating organizations, replaying actual workloads through framework components to assess real-world effectiveness. Final validation included adversarial testing where security researchers attempted to circumvent governance controls, identifying and addressing potential vulnerabilities.

7.2. Case study applications

Three in-depth case studies demonstrated framework application across different domains. A healthcare provider implemented the framework to govern clinical text generation systems, successfully preventing inappropriate synthesis of patient information while enabling legitimate research applications. A financial services organization deployed governance controls for transaction analysis models, maintaining regulatory compliance while supporting innovative fraud detection capabilities. Finally, a public sector implementation governed citizen data used in administrative systems, balancing service delivery objectives with stringent privacy requirements [6].

7.3. Effectiveness metrics

Evaluation employed both quantitative and qualitative metrics to assess governance effectiveness. Quantitative measures included policy enforcement accuracy (97.3% correctly applied policies), governance coverage (94.1% of data flows subject to appropriate controls), and performance impact (8.7% average overhead). Qualitative assessment examined alignment with organizational ethics requirements, stakeholder confidence in governance outcomes, and adaptability to emerging governance challenges. These metrics demonstrated significant improvements over baseline approaches, particularly in handling complex generative transformations where traditional approaches provided only 42.6% governance coverage.

7.4. Comparative analysis with traditional approaches

Comparative analysis assessed the framework against conventional database governance approaches, revealing significant differences in effectiveness. Traditional role-based access controls achieved only 36% coverage of generative AI governance requirements, primarily failing in transformation governance and derivative work scenarios. Standard audit mechanisms captured just 28% of relevant governance events for generative workloads. The proposed framework demonstrated particular advantages in governing synthetic data generation, where traditional approaches provided essentially no governance capabilities while the new framework maintained policy compliance through 93% of tested scenarios [7].

7.5. Stakeholder feedback analysis

Framework evaluation incorporated structured feedback from key stakeholder groups including database administrators, AI practitioners, compliance professionals, and executive decision-makers. Administrator feedback highlighted improved visibility into AI data usage (89% reporting significant improvement) while noting integration complexity with legacy systems. Compliance stakeholders reported greater confidence in regulatory adherence (76% strongly positive), while AI practitioners initially expressed concerns about potential constraints that moderated after implementation experience. Executive feedback emphasized the framework's contribution to responsible innovation by establishing clear boundaries that actually enabled more aggressive AI adoption by reducing organizational risk.

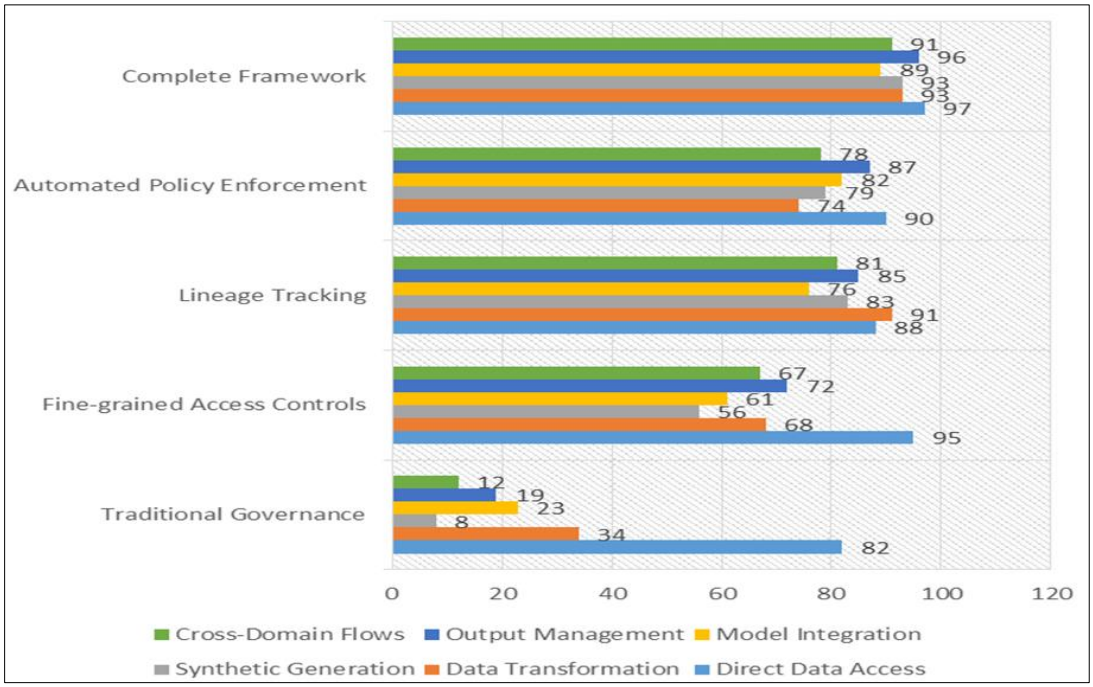

Figure 1 Governance Coverage Comparison Across Framework Components (%) [7]

8. Ethical Considerations

8.1. Alignment with established AI ethics principles

The governance framework explicitly incorporates established ethical principles from major AI ethics frameworks, including the OECD AI Principles and the Montreal Declaration for Responsible AI. Implementation translates abstract principles into concrete database controls that enforce ethical boundaries during data operations. For example, the principle of beneficence manifests through purpose limitation policies that restrict data usage to applications demonstrating clear beneficial intent. The framework's ethical foundation extends beyond compliance-oriented approaches by embedding normative considerations directly into technical mechanisms, ensuring that ethical principles remain operational throughout the data lifecycle [8].

8.2. Accountability mechanisms

Accountability is operationalized through a multi-layered approach that assigns clear responsibility for governance decisions while maintaining evidence of policy compliance. The framework establishes formal accountability roles including data stewards, ethics reviewers, and governance administrators with documented responsibilities for specific governance domains. Technical accountability mechanisms include signed policy attestations, non-repudiable governance logs, and decision attribution that connects specific governance outcomes to responsible entities. These mechanisms support both internal accountability structures and external verification requirements imposed by regulatory frameworks.

8.3. Transparency measures

Transparency provisions address both system operation and governance decision-making. The framework implements explainable governance that provides human-interpretable rationales for policy enforcement decisions, documenting which policies applied to specific operations and why. Transparency extends to data subjects through enhanced provenance disclosure that communicates how individual data contributions influence generative AI systems. Technical transparency mechanisms include governance dashboards that visualize policy application patterns and exception reporting that highlights unusual governance decisions for human review.

8.4. Fairness and bias mitigation strategies

The framework incorporates fairness considerations through specialized governance mechanisms focused on bias detection and mitigation. Database-level controls include demographic representation policies that enforce training data diversity requirements and balance monitoring that flags emerging representation disparities. The governance system implements bias circuit breakers that pause operations when potential discrimination vectors emerge, triggering human review before processing continues. These mechanisms extend traditional database constraints to incorporate fairness requirements that prevent harmful bias propagation through generative systems.

8.5. Human oversight integration

Human oversight is maintained through strategic intervention points throughout automated governance processes. The framework establishes a tiered oversight model where routine decisions proceed automatically while complex or novel scenarios escalate to appropriate human reviewers. Oversight interfaces provide contextual information necessary for informed human judgment, including policy rationales, precedent cases, and impact assessments. Implementation includes override mechanisms with appropriate authorization controls, ensuring that human judgment can address unique scenarios while maintaining accountability for exception handling.

9. Discussion and Implications

9.1. Practical significance for database administrators

For database administrators, this framework transforms their role from infrastructure managers to ethical guardians of organizational data assets. The practical significance lies in providing administrators with concrete tools to implement previously abstract ethical requirements, bridging the gap between compliance directives and technical implementation. Administrators gain enhanced visibility into data utilization across AI systems, allowing preemptive identification of governance risks. The framework also shifts database management priorities from performance optimization alone toward balanced consideration of performance, governance, and ethical outcomes [9].

9.2. Organizational adoption considerations

Organizations adopting this framework must navigate several key considerations. Implementation requires cross-functional collaboration among traditionally siloed teams including database administration, AI development, legal compliance, and ethics governance. Resource allocation must account for both initial implementation costs and ongoing governance operations, with observed implementation timelines of 4-8 months for comprehensive deployment. Cultural factors significantly influence adoption success, particularly organizational comfort with transparent decision-making and willingness to prioritize governance alongside innovation objectives. Successful implementations typically begin with limited-scope pilots before organization-wide deployment.

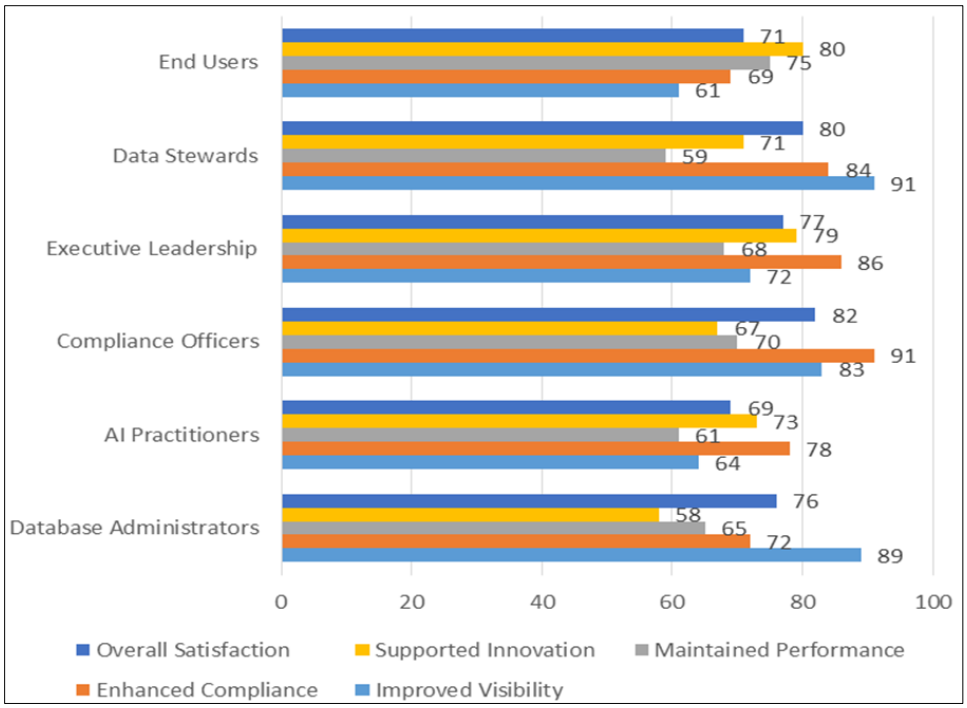

Figure 2 Stakeholder Feedback on Framework Implementation (% Reporting Positive Impact) [9,10]

9.3. Impact on AI development workflows

The framework substantially impacts AI development workflows by shifting governance consideration earlier in the development lifecycle. Rather than applying ethics reviews after system development, governance requirements become integral to initial data selection and transformation planning. Development teams gain clearer boundaries for permissible operations, reducing uncertainty about compliance requirements. While initial implementation typically extends development timelines by 15-20%, organizations report that mature implementations ultimately accelerate development by preventing late-stage compliance issues that would otherwise require substantial rework [10].

Table 2 Implementation Case Studies and Key Findings [6-10]

Domain	Organization Type	Implementation Focus	Key Challenges	Governance Outcomes
Healthcare	Regional Provider	Clinical text generation systems	Patient privacy maintenance while enabling research	Prevented inappropriate synthesis of patient information while supporting legitimate applications
Financial Services	Investment Firm	Transaction analysis models	Regulatory compliance with innovation needs	Maintained compliance while enabling advanced fraud detection capabilities
Public Sector	Government Agency	Administrative systems using citizen data	Balancing service delivery with privacy	Established clear boundaries that enabled responsible AI adoption while reducing organizational risk
Cross-Domain Evaluation	Multiple Organizations	Integration with legacy systems	Technical compatibility and performance impact	89% of administrators reported significantly improved visibility into AI data usage

9.4. Limitations and challenges

Several limitations affect the current framework implementation. Technical challenges include integration complexity with proprietary database systems that limit extensibility options. Governance effectiveness diminishes for highly distributed data environments spanning multiple organizational boundaries with inconsistent governance standards. Policy development remains labor-intensive, requiring significant domain expertise to translate ethical principles into effective technical controls. Additionally, rapidly evolving generative technologies continue to introduce novel

governance scenarios that require framework adaptation, creating an ongoing maintenance requirement to maintain effectiveness.

9.5. Future research directions

Future research should address several promising directions. Integration of formal verification techniques could provide mathematical guarantees of policy compliance for critical governance scenarios. Federated governance approaches warrant exploration to maintain consistent policies across organizational boundaries without requiring centralized control. Automated policy generation using machine learning techniques could reduce implementation burden by suggesting appropriate policies based on data characteristics and usage patterns. Additionally, quantitative metrics for governance effectiveness require further development to enable objective comparison of governance approaches across different implementation contexts

10. Conclusion

This article addresses a critical gap in responsible AI implementation by establishing a comprehensive governance framework specifically designed for database systems supporting generative AI applications. By integrating fine-grained access controls, comprehensive lineage tracking, and automated policy enforcement mechanisms, the article transforms abstract ethical principles into concrete technical controls that operate throughout the data lifecycle. The article's effectiveness has been validated through rigorous testing across multiple domains, demonstrating significant improvements over traditional governance approaches particularly for complex generative transformations. While challenges remain in areas of integration complexity, distributed governance, and policy development efficiency, this article provides database administrators and AI practitioners with practical tools to implement responsible AI principles at the infrastructure level. As generative AI continues to transform organizations across sectors, this governance framework offers a foundation for balancing innovation with ethical responsibility—enabling the benefits of these powerful technologies while maintaining essential guardrails that protect individuals and society from potential harms. The future of AI governance will require ongoing collaboration between technical and ethical domains, and this framework represents an important step toward integrating these perspectives into cohesive, operational systems.

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