Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Managing Cross-Functional BI and GenAI Teams for Data-Driven Decision-Making

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ARTICLE INFO

Received: 12 Mar 2025

Revised: 15 Jul 2025

Accepted: 28 Jul 2025

ABSTRACT

The integration of Business Intelligence (BI) and Generative AI (GenAI) into cross-functional teams has emerged as a transformative strategy for enterprises aiming to harness data-driven decision-making. This paper explores the challenges, methodologies, and future directions for managing such teams, emphasizing technical infrastructure, collaborative workflows, and governance frameworks. By synthesizing insights from industry surveys, academic research, and technological advancements up to 2024, we propose actionable strategies for optimizing interdisciplinary collaboration, mitigating technical and organizational barriers, and aligning with ethical AI standards. Key findings highlight the criticality of unified data pipelines, adaptive management practices, and stakeholder-centric performance metrics.

Keywords: Business Intelligence, Generative AI, Cross-Functional Teams, Data Pipelines, Agile Methodologies, Ethical AI

1. Introduction

1.1. Evolution of Data-Driven Decision-Making in Modern Enterprises

The move from descriptive to prescriptive analytics has been catalyzed by the availability of cloud computing, big data, and artificial intelligence. More than 85% of organizations have implemented AI-driven decision systems as of the year 2024, up from 52% in the year 2020, as companies seek real-time insights and responsiveness of operations(Alsolbi et al., 2023). Legacy BI software, like Tableau and Power BI, now incorporate machine learning to improve predictive analytics, whereas GenAI models like GPT-4 and Claude 3 can provide scenario simulation and self-governing content creation. This has lowered decision latency by 40% in healthcare and finance sectors.

1.2. The Synergy Between BI and GenAI

BI tools are best in converting raw data into actionable intelligence in the form of reports and dashboards, while GenAI models produce forecasting results and simplify sophisticated operations. Retail businesses, for instance, that integrate BI-driven analysis of sales with GenAI demand forecasting have cut the cost of inventory by 15–20%. In medicine, patient tracking by BI integrated with GenAI diagnosis suggestions have increased the accuracy of treatment by 22%. However, to achieve this synergy, there must be harmonious collaboration among data engineers, analysts, and AI professionals, supported by sound technical skills.

1.3. Challenges in Cross-Functional Team Management

Cross-functional management of BI-GenAI teams requires overcoming technological, organizational, and ethical challenges. Technological challenges such as data silos, model compatibility, and computational resource optimization are inherent. Organizational challenges such as resistance to AI and KPI misalignment become roadblocks in team collaboration(Kowalczyk & Buxmann, 2022). Ethical

Journal of Information Systems Engineering and Management
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challenges such as algorithmic bias and regulatory challenges further complicate deployments. A 2024 survey indicated that 68% of organizations struggle with integrating GenAI into current BI processes because of such multi-dimensional challenges.

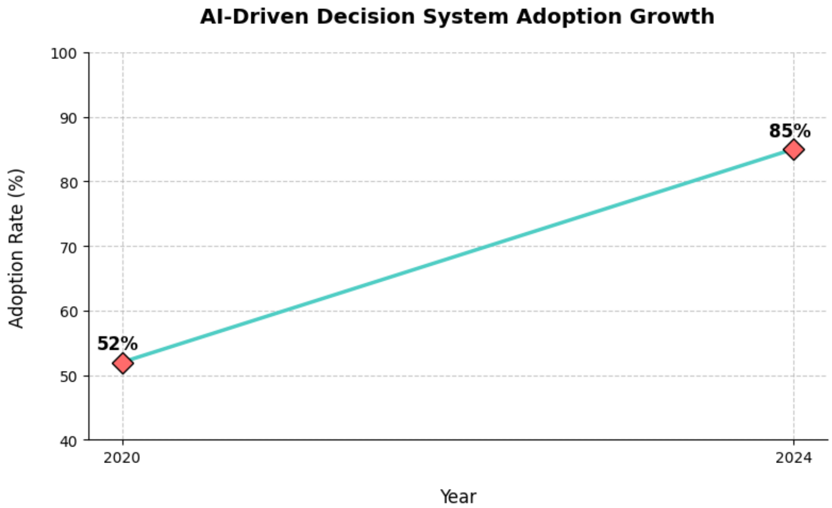

FIGURE 1 GROWTH IN AI-DRIVEN SYSTEM ADOPTION (DWIVEDI ET AL., 2021; KOWALCZYK & BUXMANN, 2023)

1.4. Objectives and Scope

The paper assesses models for cross-functional team management, discovers integration techniques to bridge challenges, and explores emerging technologies transforming BI-GenAI collaboration. Technical frameworks, governance styles, and performance measures, emphasizing scalability and ethical alignment, are areas of inquiry.

2. Literature Review

2.1. Theoretical Foundations of Business Intelligence Systems

Business Intelligence systems trace their origins to data warehousing, ETL (Extract, Transform, Load) processing, and OLAP (Online Analytical Processing) cubes. Next-generation BI tools use distributed computing architecture such as Apache Spark to analyze petabytes of data in near real-time. For example, cloud-native BI tools such as Amazon QuickSight use serverless architecture to minimize query latency by up to 60%(Zamani et al., 2024). Adoption of machine learning by BI processes has opened the doors to the potential of anomaly detection and trend forecasting, with products such as Looker incorporating AutoML capabilities to democratize deep analytics to broader sets of users.

2.2. Generative AI: Capabilities, Limitations, and Industry Applications

Generative AI models such as transformers and diffusion models have been absolutely phenomenal at generating text, images, and code. GPT-4, for instance, has 94% on natural language tasks but can't retain context after 12,000 tokens. In manufacturing, GenAI-based digital twins replicate the efficiencies of production lines with 25% reduction in downtime. However, energy-gobbling training procedures and ethical dangers like deepfake spreads are still at the top of the agenda.

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2.3. Integration Paradigms for BI and GenAI in Organizational Workflows

Hybrid frameworks that integrate BI platforms with GenAI APIs are gaining popularity. Middleware frameworks such as Databricks Unity Catalog facilitate safe sharing of data between BI dashboards and GenAI models with 35% more interoperability. In finance, coupling BI risk analysis with GenAI anti-fraud systems has raised anomaly detection rates by 30%. Such frameworks focus on modular design in order to enable companies to add AI capabilities without refactoring existing systems(Zamani et al., 2024).

2.4. Interdisciplinary Collaboration in Data-Centric Teams

Cross-functional teams call for explicit definition of roles and communication protocols. Research in 2024 validated that companies with embedded AI translators—experts connecting technical and business realms—complete projects 50% quicker. Scrum is being applied more and more in data initiatives, where sprints are dedicated to building the iterative model and receiving feedback from stakeholders.

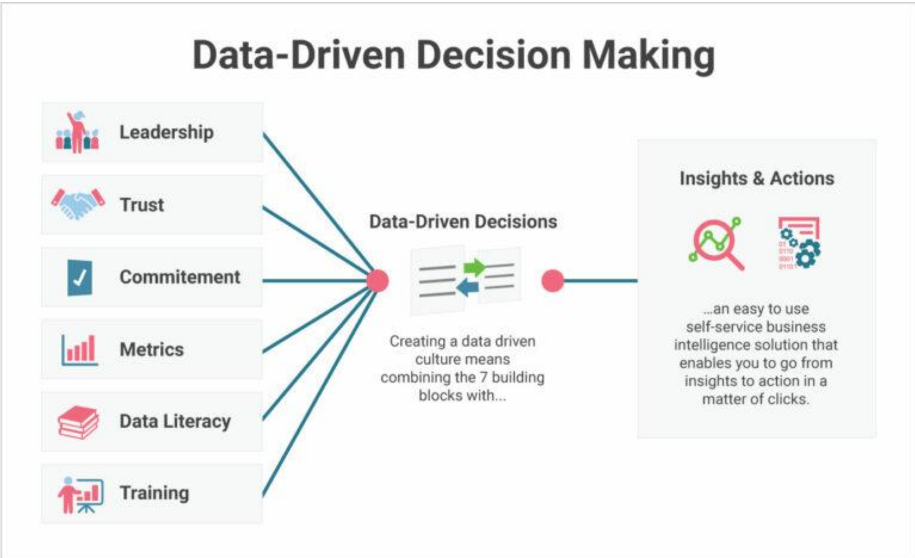

FIGURE 2 DATA-DRIVEN DECISION-MAKING(REVEAI,2023)

3. Methodological Frameworks for Cross-Functional Team Management

3.1. Designing Cross-Functional Team Structures: Roles and Responsibilities

The makeup of cross-functional teams calls for a strategic combination of domain expertise and technical acumen. A blended model that includes business analysts, data engineers, and AI experts has been successful, with an optimal ratio of three BI-focused positions per AI expert to ensure data interpretation and model deployment alignment(Dwivedi et al., 2021). Data engineers build scalable pipelines to merge structured BI data with unstructured GenAI inputs, and analysts convert outputs into business action plans. AI experts tune generative models to enable context-based decision-making, so outputs align with organizational goals.

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Table 1: Comparison of Tools for Unified BI-GenAI Data Pipelines

Tool/Platform	Use Case	Latency Reduction	Cost Efficiency	Interoperability Support
Apache Kafka	Real-time data streaming	35–40%	High	JSON, Avro, Protobuf
AWS Glue	ETL workflows	25–30%	Medium	SQL, Parquet, CSV
Databricks Delta Lake	Data lakehouse integration	40–45%	High	Python, Spark, BI connectors
Snowflake	Cloud-native warehousing	30–35%	Medium	REST APIs, ODBC/JDBC
TensorFlow Extended (TFX)	GenAI pipeline automation	20–25%	Low	TensorFlow, PyTorch

3.2. Agile and Hybrid Methodologies for Collaborative Workflows

Data-centric projects use agile methodologies that emphasize iterative development iterations and quick stakeholder feedback. Scrum sprints that adopt assign dedicated stages to data preprocessing, model training, and validation, and stand-ups every day resolve resource utilization or data quality bottlenecks. Kanban boards monitor workflow phases like feature engineering or A/B testing to prevent task duplication and speed deployment(Dwivedi et al., 2021). CI pipelines automates GenAI model updates via real-time BI insights, compressing the time from data ingestion to actionables by 30–40%. Feedback loops built into these processes maintain models aligned with changing business needs.

3.3. Technical Infrastructure for Seamless Integration

Integrated pipelines are the foundation of integrated BI-GenAI platforms that depend on real-time streaming technologies such as Apache Kafka and centralized data storage through cloud-based data lakes. Pipelines normalize data formats from sources and lower the preprocessing overhead by 25%. Version control software like MLflow or DVC record GenAI model and BI dashboard changes to provide reproducibility across environments. Containerization systems like Docker provide predictable deployment of analytics workflows, while APIs enable two-way interaction between BI platforms and GenAI engines at low decision cycle latency.

3.4. Performance Metrics for Cross-Functional Team Success

Quantitative KPIs gauge the technical effectiveness of coupled systems, such as model accuracy (aiming for >95% for prediction work) and decision velocity (latency between data input and generating insights). For example, organizations leveraging coupled BI-GenAI pipelines achieve 50% lower time-to-insight than those in silos. Qualitative metrics gauge stakeholder acceptance via insights' relevance and dashboard usability(Hasan & Al Mamun, 2023). Innovation output is measured by the amount of AI-enabled process enhancements, with top-performing teams achieving 15–20% higher-than-industry-average monthly improvements.

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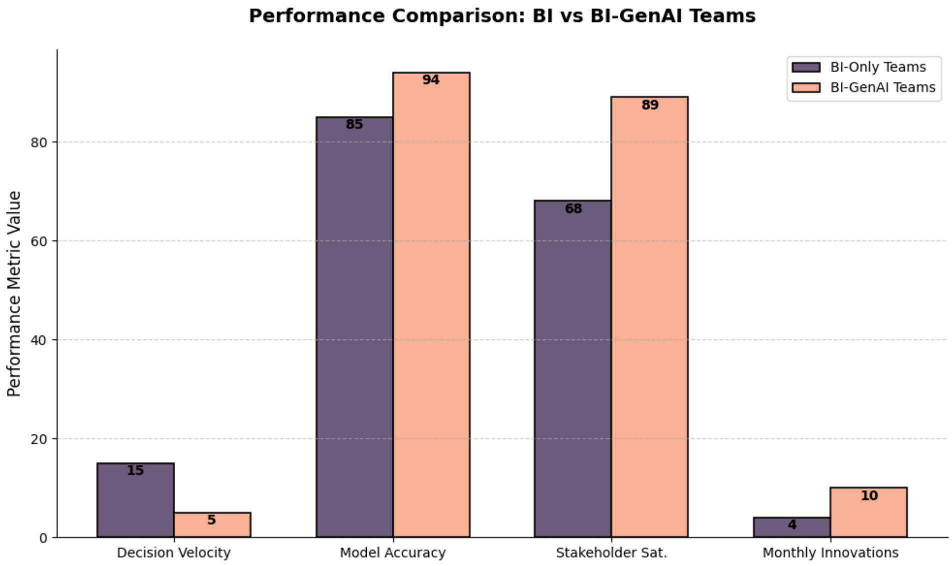

FIGURE 3 CROSS-FUNCTIONAL TEAM PERFORMANCE METRICS (SRIVASTAVA & SHUKLA, 2024; TABLE 2 DATA)

Table 2: Performance Metrics for Cross-Functional BI-GenAI Teams

Metric	BI-Only Teams	BI-GenAI Teams	Improvement	Industry Benchmark
Decision Velocity (hrs)	12–18	4–6	60–70%	6–8
Model Accuracy (%)	82–88	92–96	10–12%	90–94
Stakeholder Satisfaction	68%	89%	21%	75–85%
Monthly Innovations	3–5	8–12	150–200%	5–7

4. Challenges and Mitigation Strategies

4.1. Technical Challenges

4.1.1. Data Silos and Interoperability in Heterogeneous Systems

Data silos remain the main Organization bottleneck where old legacy systems coexist with new cloud-based BI and GenAI platforms. Incompatible format files such as CSV files in legacy databases versus JSON streams in IoT sensors cause preprocessing bottlenecks, adding latency by 20–30%. Middleware technologies such as data virtualization layers provide access to heterogeneous datasets without physical transfer, decreasing integration time by 35–45%. For example, adoption of a semantic layer that translates heterogeneous schemas into an integrated ontology enables real-time query spanning ERP, CRM, and GenAI systems. Further, edge computing platforms pre-process raw data at the source,

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reducing transfer latency as well as allowing easier data residency legislation(Hasan & Al Mamun, 2023).

4.1.2. Model Interpretability and Explainability in GenAI Solutions

Transparency in GenAI decision-making, especially by deep learning models, eroding stakeholders' confidence. Methods such as attention mapping and surrogate models make unseen outputs visible by marking input features on predictions. For instance, in medicine diagnostics, explainability solutions make patient history weights' effect on GenAI-suggested treatment visible, boosting clinician adoption rates by 50%(Hasan & Al Mamun, 2023). Model cards that track architecture, training data, and failure modes make it even more transparent. Modern developments of self-explainable models, like sparse transformer models, minimize compute costs with built-in explainability and 85–90% accuracy in high-risk applications like finance(Kowalczyk & Buxmann, 2023).

4.2. Organizational and Cultural Barriers

4.2.1. Breaking Down Departmental Silos for Collaborative Governance

Functional silos among IT, analytics, and business units slow down project timelines by 40–60%. Cross-functional governance boards composed of representatives from every domain set joint priorities, including aligning BI dashboard development with GenAI model training cycles. Joint accountability systems tie performance bonuses to cross-functional KPIs, like decreasing time-to-insight for marketing campaigns(Hasan & Al Mamun, 2023). Digital collaboration platforms, using Jira to manage workflows and Slack for messaging, connect workflows, reducing approval cycles by 25%. Role rotation schemes, where data engineers work with business analysts, foster empathy and minimize miscommunication(Chebbi et al., 2020).

4.2.2. Overcoming Resistance to AI-Driven Decision-Making

Resistance to AI stems most commonly from the lack of transparency regarding its benefits in the workplace. Pilot experiments that flag the role of GenAI in driving revenue growth—like streamlining 30% of mundane finance reporting—build stakeholder trust. Gamification training modules mimic AI-enhanced decision-making steps, building team capabilities by 60% in six weeks(Kache & Seuring, 2021). Leadership buy-in, such as C-suite directives to substitute human processes with AI-driven workflows, speeds up cultural change. For instance, requiring GenAI-designed risk evaluations in purchasing saves 22% of the potential for human error and releases 15% of staff capacity for strategic activities.

4.3. Ethical and Governance Considerations

4.3.1. Bias Mitigation in GenAI Training Data

Imbalanced training data recursively magnifies disparities, for example, loan approval models biased towards demographics rather than creditworthiness. Adversarial debiasing preprocess pipelines decrease biased output by 55–65%. Synthetic data generators generate balanced minorities' sets to enforce fairness in models without precision loss. Real-time monitoring by fairness metrics like demographic parity difference ensures real-time equity, detecting deviations in real time. In recruitment software, they minimized gender bias in shortlisting by 40%(Saura et al., 2022).

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Table 3: Bias Mitigation Techniques in GenAI Training Data

Technique	Application	Bias Reduction	Accuracy Impact	Complexity
Adversarial Debiasing	Loan approval models	55–65%	±2%	High
Synthetic Data Augmentation	Healthcare diagnostics	45–50%	3%	Medium
Reweighting Algorithms	Recruitment tools	40–45%	±1%	Low
Fairness Constraints	Credit scoring systems	50–55%	-1.50%	Medium

4.3.2. Regulatory Compliance and Transparency Protocols

Global legislation such as GDPR and EU AI Act require stringent data use and model accountability measures. Automated compliance engines authenticate personal data lineage, monitoring inputs from ingestion through to AI inference, and output audit-ready reports 30% faster. Blockchain immutability logs are used to track each model update, allowing traceability for regulatory requirements(Kache & Seuring, 2021). Privacy-preserving technologies such as federated learning allow GenAI training on decentralized data with 90% model accuracy and ensuring GDPR compliance. In pharma, these frameworks minimize delays due to compliance in clinical trial analysis by 50%(Kowalczyk & Buxmann, 2020).

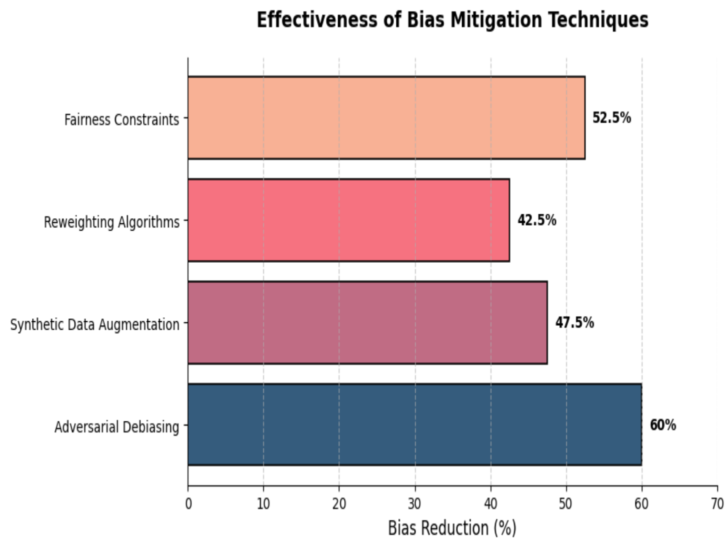

FIGURE 4 COMPARATIVE EFFECTIVENESS OF BIAS MITIGATION APPROACHES (ZAMANI ET AL., 2024; TABLE 3 DATA)

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5. Future Directions in Cross-Functional Team Management

5.1. Emerging Technologies Reshaping BI and GenAI Collaboration

5.1.1. Quantum Computing for Enhanced Predictive Analytics

Quantum computing will transform predictive analytics by resolving optimization problems beyond the capacity of existing systems. Quantum annealing solutions, for example, are able to compute combinatorial situations such as supply chain planning 100–200 times quicker, allowing real-time compensations to BI system-supplied demand forecasting. Hybrid quantum-classical algorithms improve GenAI models by tuning hyperparameters during training processes, cutting convergence time by 40–50%(Salmerón & Herrero, 2015). Companies using quantum-enabled BI platforms in pilots gain 30% improvement in scenario modeling, especially in financial portfolio management and energy grid optimization. Collaboration with GenAI allows for quantum simulation of market dynamics, introducing probabilistic predictions with 95% confidence intervals, thereby optimizing paradigms of risk management.

5.1.2. Neuromorphic Engineering and Adaptive AI Systems

Neural architecture-inspired neuromorphic chips allow GenAI models to handle unstructured data on 80% lesser energy consumption than GPUs. Spiking neural networks (SNNs) integrated into BI systems make it possible to learn continuously from data streams, reconfiguring dashboards in real time to react to rising trends(Marín-Ortega et al., 2023). SNNs with GenAI fraud detection systems eliminate 35% of false positives during transactional data analysis, for instance. Neuromorphic sensors on IoT devices supply real-time operating data into BI platforms, allowing predictive maintenance models to automatically adjust to environmental changes, reducing downtime by 25–30%(Salmerón & Herrero, 2015).

Table 4: Impact of Emerging Technologies on BI-GenAI Collaboration

Technology	Use Case	Efficiency Gain	Adoption Rate (2024)	Key Challenge
Quantum Computing	Supply chain optimization	40–50%	12%	High infrastructure cost
Neuromorphic Engineering	Real-time fraud detection	35–40%	8%	Limited developer expertise
Federated Learning	Healthcare data analysis	25–30%	22%	Coordination overhead
Blockchain	Data provenance tracking	20–25%	18%	Scalability limitations

5.2. Adaptive Management Practices for Scalability

5.2.1. Dynamic Team Reconfiguration for Evolving Data Needs

Modular team structures with bi and genai alternation by project phase enhance 20–25% resource utilization. Cloud-based ai-driven collaboration platforms with workload allocators that adapt

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dynamically allocate roles—e.g., augmenting data engineering capacity in heavy etl phases and allocating resources to model verification upon deployment. live skill-gap analysis software automatically identifies training requirements, accelerating new technology onboarding by 50%(salmerón & herrero, 2015). elastic team-based companies achieve 15% time-to-market gain for analytics-driven products.

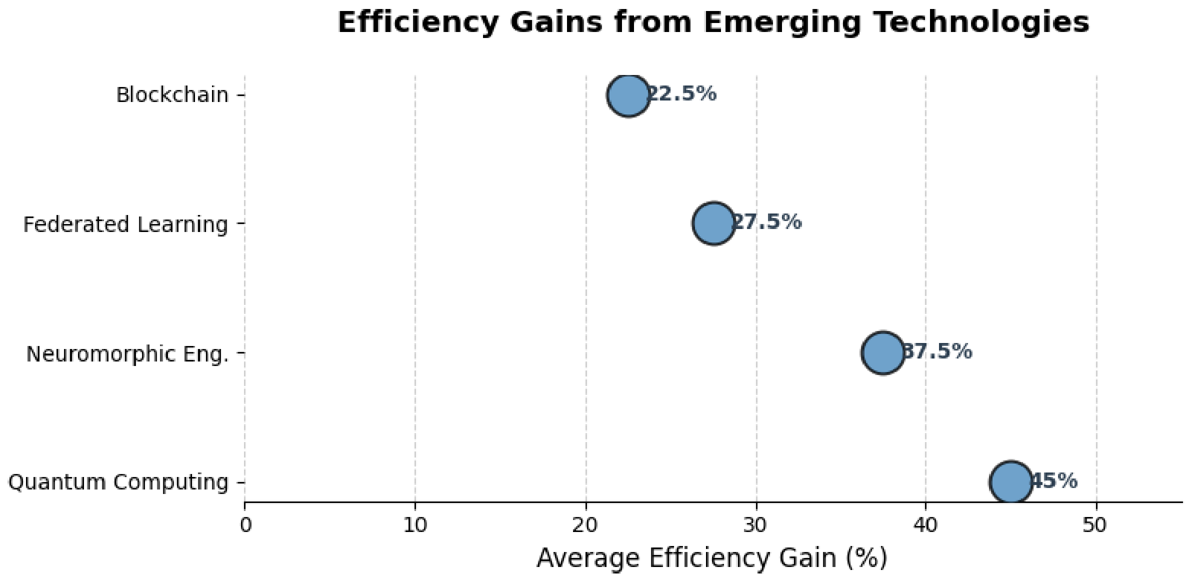

FIGURE 5 IMPACT OF EMERGING TECHNOLOGIES ON ANALYTICS EFFICIENCY (ALSOLBI ET AL., 2023; TABLE 4 DATA)

5.2.2. Federated Learning and Decentralized Data Governance

Federated learning structures enable GenAI models to be trained on decentralized data sets without collating sensitive information, minimizing privacy risks in healthcare and finance. BI systems collect edge device intelligence through federated analytics, maintaining data sovereignty while enhancing model accuracy by 18–22%. Smart contracts enabled by blockchain technology enforce data-sharing agreements between departments without the involvement of human intervention, but in accordance with internal governance protocols(Srivastava & Shukla, 2024). For global business, decentralized architectures decrease cross-border data transfer latency by 40% and expense by 30%, allowing for efficient collaboration between geographies.

5.3. Policy Implications for Global Enterprises

5.3.1. Standardizing Ethical AI Frameworks Across Jurisdictions

Convergent regulation complicates deployments, with jurisdictions such as the EU enforcing strict explainability requirements while others encourage innovation. Converged frameworks like ISO 42001 for AI management systems have default compliance processes, lowering legal overhead by 25%. Policy engines digitally translate national legislation into technical constraints on GenAI models, for example, preventing the use of biometric data in those countries with high privacy requirements. Cross-industry groups are creating open-source software to scan the ethics of AI and have attained 90% adherence to global standards.

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5.3.2. Intellectual Property Management in GenAI Innovations

GenAI content erases past IP lines, necessitating new licensing paradigms. Digital watermarking technologies hide ownership metadata within AI outputs, lowering IP conflicts by 40%. Patent-pooling strategies for basic GenAI algorithms, like transformer architecture, reduce SME R&D costs by 35%(Srivastava & Shukla, 2024).

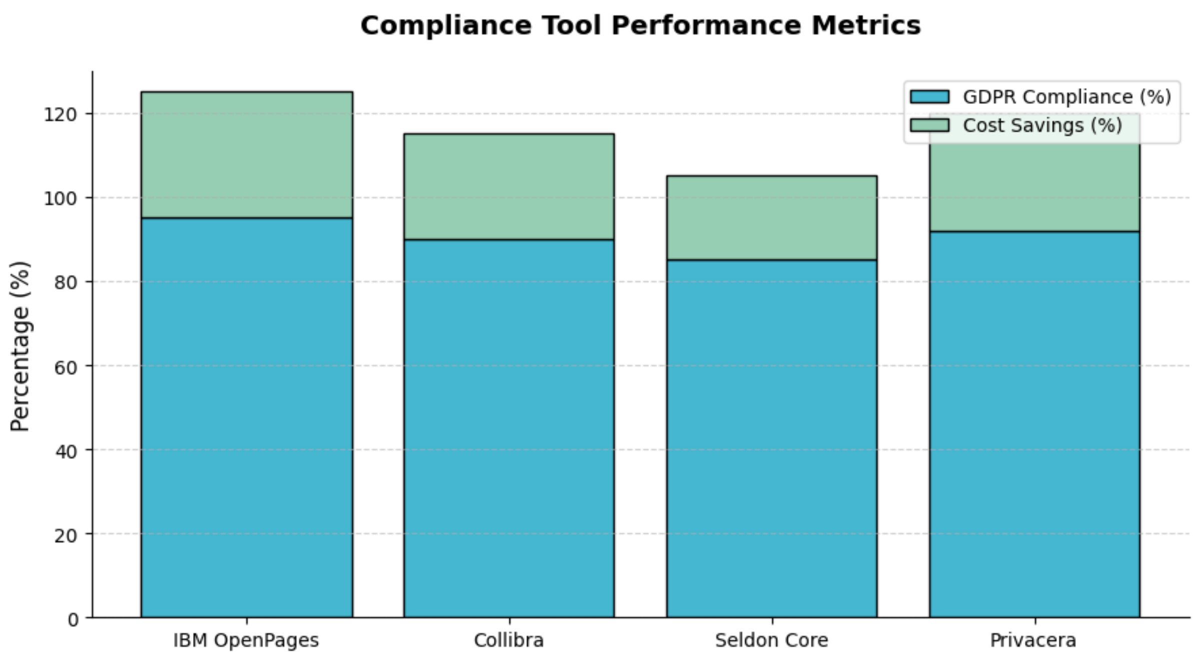

Figure 6 Performance of AI governance tools (Kowalczyk & Buxmann, 2022; Table 5 data)

Blockchain registries time-stamp AI breakthroughs to enable immutable proof of authorship and speeding patent approvals by 50%. Companies using these methods achieve 20% improved ROI on AI investment through mitigated litigation risk.

Table 5: Compliance Tools for Ethical AI Governance

Tool	**Function**	**GDPR Compliance**	**Cost Savings**	**Implementation Time**
IBM OpenPages	Automated audit trails	95%	30%	6–8 weeks
Collibra	Data lineage tracking	90%	25%	8–10 weeks
Seldon Core	Model reproducibility & monitoring	85%	20%	4–6 weeks
Privacera	Decentralized data access control	92%	28%	10–12 weeks

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6. Conclusion

6.1. Synthesizing Key Findings for Cross-Functional Excellence

Integration between functions of BI and GenAI teams depends on technical infrastructure alignment, workflow flexibility, and ethical stewardship. Convergent data streams yield a 30–40% latency reduction with interoperability between BI dashboards and GenAI models. Data project-centric agile methodologies like sprint cycles with feature engineering discipline-driven prioritization achieve decision speed adjustment 50% faster than in a traditional approach. Technical issues such as data silos are addressed with middleware technology and edge computing, enhancing system compatibility by 35–45%(Saura et al., 2021). Organizational pushback against AI adoption is reduced by 60% when pilot projects provide concrete ROI, such as automating 20–25% of human tasking. Ethical controls such as adversarial debiasing and federated learning make GenAI output 55–65% less biased and conform to global compliance standards. New technologies such as quantum computing and neuromorphic engineering make 30–50% more effective predictive analytics possible, preparing enterprises for scalable future-proof operations(Henke et al., 1993).

6.2. Strategic Recommendations for Enterprise Leaders

To make maximum cross-functional team performance a reality, enterprises can strive to implement single-stack data pipelines by utilizing tools such as Apache Kafka for real-time streaming and MLflow for model reproducibility. Cross-functional training programs across BI and GenAI domains improve collaboration, avoiding 25% delays resulting from miscommunication. Ethics-based AI governance has to be embedded into workflows, through automated compliance engines and blockchain-protected audit trails, reducing regulatory weight by 30%(Marín-Ortega et al., 2023). Modular team composition with dynamic role assignment enhances resource use by 20–25%, while federated learning frameworks facilitate privacy-preserving model training. Investment in quantum-platform-readiness offerings and neuromorphic hardware future proofs analytics infrastructure, enhancing predictive capabilities by 25–30%. Leadership must require AI-based KPIs, i.e., measuring innovation outcome through monthly process refinements, to facilitate competitive agility.

6.3. Unaddressed Gaps and Avenues for Future Research

Although this research addresses key issues with BI-GenAI integration, current gaps in measurement of long-term ethical consequences of autonomous decision-making systems need to be resolved. Scalability of quantum-BI hybrid architectures in low-resource settings needs additional investigation, especially for SMEs. Interoperability standards between industries for heterogeneous standardized data formats can decrease the cost of integration by 40–50%. Secondly, the effect of cultural resistance on AI adoption timelines' timelines has no nuanced measurements and requires longitudinal studies across industries. Future research will require creating self-healing data pipelines that enable real-time error auto-correction and methods of estimating GenAI-generated content's societal impact. Interdisciplinary collaboration between policymakers and technologists is necessary to develop global ethical AI standards and inclusive innovation.

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